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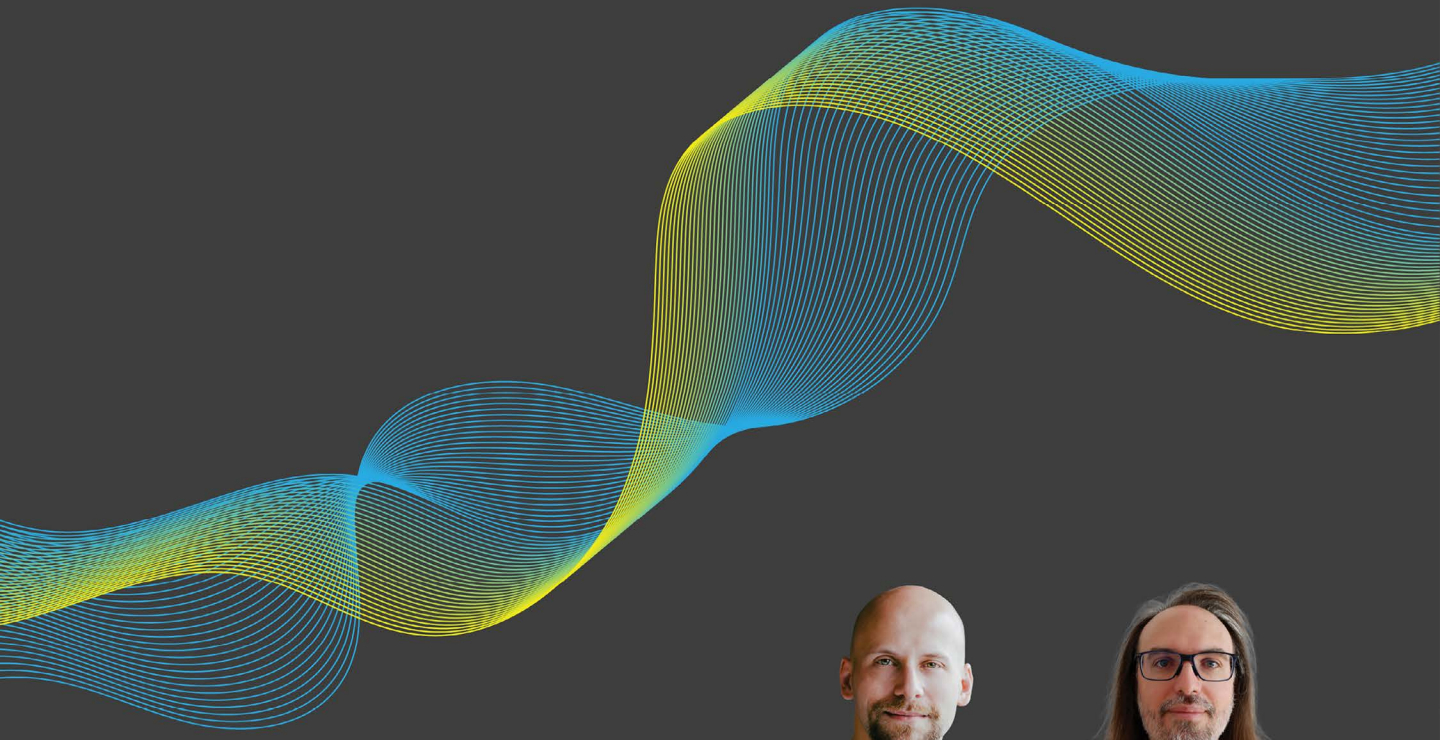
Learn Python Programming

A comprehensive, up-to-date, and definitive guide to learning Python



Fourth Edition

Fabrizio Romano
Heinrich Kruger

‹packt›

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To Margherita e Graziano, cuore del mio cuore. Thank you for all the love, help, and advice you've given me in the past twenty years

– Fabrizio Romano

To my wife, Debi, without whose love, support, and endless patience, I would not have been able to do this

– Heinrich Kruger

Contributors

About the authors

Fabrizio Romano was born in Italy in 1975. He holds a master's degree in computer science engineering from the University of Padova. He's been working as a professional software developer since 1999. Fabrizio has been working at Sohonet since 2016, where he currently serves as a development manager. In 2020, the Television Academy honored him and his team with an Emmy Award in Engineering Development for advancing remote collaboration.

I would like to thank all the people at Packt, in particular Amisha Vathare for her professionalism and kindness. Thanks to Stefano and Javier, the reviewers, for their insightful comments, and to Heinrich. To my wife Elisa goes my deepest gratitude: thank you for your love and support.

Heinrich Kruger was born in South Africa in 1981. He holds a master's degree in computer science from Utrecht University in the Netherlands. He has been working as a professional software developer since 2014. Heinrich has been working alongside Fabrizio in the Product Team at Sohonet since 2017. In 2020, the Television Academy honored them with an Emmy Award in Engineering Development for advancing remote collaboration.

I want to thank Fabrizio for asking me to help him with this book. It's been a great experience working with you, my friend. I would also like to thank Stefano Chinellato and Javier Navarro for their helpful comments, as well as everyone at Packt who helped us along the way. Most of all, I thank my wife Debi for all her love, encouragement, and support.

About the reviewer

Javier Muñoz was born in Valladolid, Spain, where he nurtured a deep interest in computers from an early age. He holds a degree in Telecommunications Engineering with a specialization in Telematics and a Master's degree in Big Data Science from the Universidad de Valladolid, graduating with First Class Honours.

After his studies, Javier moved to Dublin, Ireland, where he worked as a software engineer and data analyst. His career progressed when he joined Optum, a Fortune 5 healthcare technology company, where he focused on AI. At Optum, he developed and deployed AI models to enhance medical diagnosis and treatment, collaborating with healthcare professionals to improve patient outcomes while ensuring compliance with regulatory standards like HIPAA and GDPR.

In parallel with his work at Optum, Javier founded Saoi Tech Solutions, a startup that delivered large-scale machine learning solutions for multinational corporations. His projects included pioneering research in facial recognition, and he demonstrated expertise in deploying AI models at scale using advanced cloud and containerization technologies.

Currently, Javier works in the United Kingdom as a software engineer at Sohonet, where he focuses on Python-based applications written in Django, primarily for the cinema and entertainment industry. His work at Sohonet involves developing tools that facilitate collaboration and enhance production workflows in film and television.

Javier's technical expertise, particularly in Python and AI, has earned him a role as a technical reviewer for *Learn Python Programming*, *Fourth Edition*, where he ensures the content is practical, accurate, and relevant for today's programmers.

I would like to sincerely thank my friends and colleagues Fabrizio and Heinrich, the authors of this book, for their incredible support, collaboration, and the opportunity to contribute as a technical reviewer. I am also grateful to the rest of the Sohonet team, as well as my past colleagues and mentors, whose guidance has been invaluable throughout my journey. This experience has been both rewarding and enriching, and I deeply appreciate everyone who has been part of it.

Stefano Chinellato is a software engineer residing in Italy. He holds a Master's degree in Computer Science Engineering from the University of Padova. With over 15 years of experience in software development, he focuses on web applications and has a strong interest in algorithms and statistics.

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Preface

It is our great pleasure to introduce you to the fourth edition of our book. The first one came out in 2015, and since then the book has been a top seller all around the world.

Ten years ago, being a programmer meant working with certain tools, implementing certain paradigms. Today, the landscape is different. Developers tend to be even more specialized than before, and there is great focus on things like APIs, and distributed applications. We have tried to capture the current trends, and to offer you the best foundational layer we could think of, drawing from our experience as developers who work in a fast-paced industry.

Each new edition has brought about some kind of change. Obsolete chapters were removed, new ones were added, and others again have been amended to reflect the modern ways in which software is written.

This edition features three new chapters. The first one discusses the topic of type hinting. Type hinting is not new to Python, but now we feel it has become such an established practice that the book wouldn't have been complete without it.

The second one, which discusses the topic of CLI applications, steps in by replacing an old chapter that was about GUIs. Most of what we do with a computer today happens in a browser, and many desktop applications have been built, or rewritten, by leveraging browser components, so we felt that a whole chapter dedicated to GUIs was perhaps a bit obsolete.

Finally, the third one explores the topic of competitive programming.

The remaining chapters have been updated to reflect the latest additions to the language, and improved to make the presentation even simpler and more fluid, while still aiming at offering interesting examples to the reader.

The soul of the book, its essence, is still intact. It shouldn't feel like yet another Python book. It is, first and foremost, about programming. It tries to convey as much information as possible and, sometimes, when the page count couldn't allow it, it points to the resources you need to further your knowledge.

It is designed to last. It explains concepts and information in a way that should stand the test of time, for as long as possible. There is great amount of work, thinking, and meetings, that goes into making sure of that.

It is also radically different than its first edition. It is much more mature, more professional, and focuses more on the language and slightly less on projects. We think the line that strikes the balance between these two parts has been drawn in the right place.

It will require you to focus and work hard. All the code is available for download. You can clone the repository from GitHub, if you like. Please check it out. It will help you cement what you will learn when reading these pages. Code is not a static thing. It is very much alive. It changes, it morphs. You will learn much more if you take the time to explore it, change it, and break it. We have left several guidelines in the book, to help you do that.

In closing, I want to express my gratitude to my co-author, Heinrich.

This book is now as much his as it is mine. Every chapter is infused with his talent, his creativity, and the depth of his knowledge. He is also gifted with tremendous memory: he can spot a redundant piece of information in chapters that are 200 pages apart. I can't do that.

Like me, he has spent many long nights and weekends making sure everything was presented in the best possible way. It is because I have shared this journey with him, that I have so much confidence in the quality of this work.

Our advice for you is to study these pages well, and experiment with the source code. Once you are confident in your Python skills, please don't stop learning. Try to go beyond the language, transcend it. A senior developer should know certain concepts and master certain skills that cannot be contained within one language, it's just not possible. Studying other languages helps to learn how to discriminate between those features that pertain to a certain language, and others that are instead more generic, related to programming. Hopefully this book will help you get there.

Enjoy the journey and, whatever you learn, please share it with others.

Fabrizio

Who this book is for

This book is for people who have some programming experience, but not necessarily with Python. Some knowledge of basic programming concepts will be useful, although it is not a strict requirement.

Even if you already have some experience with Python, this book can still be useful to you, both as a reference to Python's fundamentals, and for providing a wide range of considerations and suggestions collected over four combined decades of experience.

What this book covers

Chapter 1, *A Gentle Introduction to Python*, introduces you to fundamental programming concepts and constructs of the Python language. It also guides you through getting Python up and running on your computer.

Chapter 2, *Built-In Data Types*, introduces you to Python built-in data types. Python has a very rich set of native data types, and this chapter will give you a description and examples for each of them.

Chapter 3, *Conditionals and Iteration*, teaches you how to control the flow of the code by inspecting conditions, applying logic, and performing loops.

Chapter 4, *Functions, the Building Blocks of Code*, teaches you how to write functions. Functions are essential to code reuse, to reducing debugging time, and, in general, to writing higher quality code.

Chapter 5, *Comprehensions and Generators*, introduces you to the functional aspects of Python programming. This chapter teaches you how to write comprehensions and generators, which are powerful tools that you can use to write faster, more concise code, and save memory.

Chapter 6, *OOP, Decorators, and Iterators*, teaches you the basics of object-oriented programming with Python. It shows you the key concepts and all the potentials of this paradigm. It also shows you one of the most useful features of the language: decorators.

Chapter 7, *Exceptions and Context Managers*, introduces the concept of exceptions, which represent errors that occur in applications, and how to handle them. It also covers context managers, which are very useful when dealing with resources.

Chapter 8, *Files and Data Persistence*, teaches you how to deal with files, streams, data interchange formats, and databases.

Chapter 9, *Cryptography and Tokens*, touches upon the concepts of security, hashes, encryption, and tokens, which are essential for writing secure software.

Chapter 10, *Testing*, teaches you the fundamentals of testing, and guides you through a few examples on how to test your code, in order to make it more robust, fast and reliable.

Chapter 11, *Debugging and Profiling*, shows you the main methods for debugging and profiling code and some examples of how to apply them.

Chapter 12, *Introduction to Type Hinting*, guides you through the syntax and main concepts of type hinting. Type hinting has become more and more popular in recent years because it enriches both the language and the tools that are part of its ecosystem.

Chapter 13, *Data Science in Brief*, illustrates a few key concepts by means of a comprehensive example, using the powerful Jupyter Notebook.

Chapter 14, *Introduction to API Development*, introduces API development using the FastAPI framework.

Chapter 15, *CLI Applications*, introduces command-line interface applications. They are run in a console or terminal, and are a common and natural way in which developers write several of their own day-to-day tools.

Chapter 16, *Packaging Python Applications*, guides you through the process of preparing a project to be published, and shows you how to upload the result on the **Python Package Index** (**PyPI**).

Chapter 17, *Programming Challenges*, introduces the concept of competitive programming, by showing you how to solve two problems from the Advent of Code website.

To get the most out of this book

You are encouraged to follow the examples in this book. You will need a computer, an internet connection, and a browser. The book is written for Python 3.12, but it should also work, for the most part, with any recent version of Python 3. We have given guidelines on how to install `Python` on your operating system. The procedures to do that normally get out of date quickly, so we recommend you refer to the most up-to-date guide on the web to find precise setup instructions. We have also explained how to install all the extra libraries used in the various chapters. No particular editor is required to type the code; however, we suggest that those who are interested in following the examples should consider adopting a proper coding environment. We have offered suggestions on this matter in the first chapter.

Download the color images

We also provide a PDF file that has color images of the screenshots/diagrams used in this book. You can download it here: `https://packt.link/gbp/9781835882948`.

Download the example code files

The code bundle for the book is hosted on GitHub at `https://github.com/PacktPublishing/Learn-Python-Programming-Fourth-Edition`. We also have other code bundles from our rich catalog of books and videos available at `https://github.com/PacktPublishing/`. Check them out!

Conventions used

There are a number of text conventions used throughout this book.

`CodeInText`: Indicates code words in text, database table names, folder names, filenames, file extensions, pathnames, dummy URLs, user input, and Twitter handles. For example: "The `as_integer_ratio()` method has also been added to integers and Booleans."

Bold: Indicates a new term, an important word, or words that you see on the screen. For instance, words in menus or dialog boxes appear in the text like this. For example: "They are immutable sequences of **Unicode code points**."

Warnings or important notes appear like this.

Tips and tricks appear like this.

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1

A Gentle Introduction to Python

> *"Give a man a fish and you feed him for a day. Teach a man to fish and you feed him for a lifetime."*
>
> *—Chinese proverb*

Computer programming, or coding, as it is sometimes known, is telling a computer to do something using a language it understands.

Computers are very powerful tools, but unfortunately, they cannot think for themselves. They need to be told everything: how to perform a task; how to evaluate a condition to decide which path to follow; how to handle data that comes from a device, such as a network or a disk; and how to react when something unforeseen happens, in the case of, say, something being broken or missing.

You can code in many different styles and languages. Is it hard? We would say *yes* and *no*. It is a bit like writing—it is something that everybody can learn. But what if you want to become a poet? Writing alone is not enough. You have to acquire a whole other set of skills, and this will involve a longer and greater effort.

In the end, it all comes down to how far you want to go down the road. Coding is not just putting together some instructions that work. It is so much more!

Good code is short, fast, elegant, easy to read and understand, simple, easy to modify and extend, easy to scale and refactor, and easy to test. It takes time to be able to write code that has all these qualities at the same time, but the good news is that you are taking the first step toward it at this very moment by reading this book. And we have no doubt you can do it. Anyone can; in fact, we all program all the time, only we are not aware of it.

Let's say, for example, that you want to make instant coffee. You have to get a mug, the instant coffee jar, a teaspoon, water, and a kettle. Even if you are not aware of it, you are evaluating a lot of data. You are making sure that there is water in the kettle and that the kettle is plugged in, that the mug is clean, and that there is enough coffee in the jar. Then you boil the water and, maybe in the meantime, you put some coffee in the mug. When the water is ready, you pour it into the mug, and stir.

So, how is this programming?

Well, we gathered resources (the kettle, coffee, water, teaspoon, and mug) and we verified some conditions concerning them (the kettle is plugged in, the mug is clean, and there is enough coffee). Then we started two actions (boiling the water and putting coffee in the mug), and when both of them were completed, we finally ended the procedure by pouring water into the mug and stirring.

Can you see the parallel? We have just described the high-level functionality of a coffee program. It was not that hard because this is what the brain does all day long: evaluate conditions, decide to take actions, carry out tasks, repeat some of them, and stop at some point.

All you need now is to learn how to deconstruct all those actions you do automatically in real life so that a computer can actually make some sense of them. You need to learn a language as well so that the computer can be instructed.

So, this is what this book is for. We will show you one way in which you can code successfully, and we will try to do that by means of many simple but focused examples (our favorite kind).

In this chapter, we are going to cover the following:

- Python's characteristics and ecosystem
- Guidelines on how to get up and running with Python and virtual environments
- How to run Python programs
- How to organize Python code and its execution model

A brief introduction to programming

We love to make references to the real world when we teach coding; we believe they help people to better retain the concepts they are learning. However, now is the time to be a bit more rigorous and see what coding is from a more technical perspective.

When we write code, we are instructing a computer about the things it has to do. Where does the action happen? In many places: the computer memory, hard drives, network cables, the CPU, and so on. It is a whole world, which most of the time is the representation of a subset of the real world.

If you write a piece of software that allows people to buy clothes online, you will have to represent real people, real clothes, real brands, sizes, and so on and so forth, within the boundaries of a program.

To do this, you will need to create and handle objects in your program. A person can be an object. A car is an object. A pair of trousers is an object. Luckily, Python understands objects very well.

The two key features any object has are **properties** and **methods**. Let us take the example of a person as an object. Typically, in a computer program, you will represent people as customers or employees. The properties that you store against them are things like a name, a social security number, an age, whether they have a driving license, an email, and so on. In a computer program, you store all the data needed in order to use an object for the purpose that needs to be served. If you are coding a website to sell clothes, you probably want to store the heights and weights as well as other measures of your customers so that the appropriate clothes can be suggested to them. So, properties are characteristics of an object. We use them all the time: *Could you pass me that pen? —Which one? —The black one*. Here, we used the color (*black*) property of a pen to identify it (most likely it was being kept alongside different colored pens for the distinction to be necessary).

Methods are actions that an object can perform. As a person, I have methods such as *speak, walk, sleep, wake up, eat, dream, write, read,* and so on. All the things that I can do could be seen as methods of the objects that represent me.

So, now that you know what objects are, that they provide methods that can be run and properties that you can inspect, you are ready to start coding. Coding, in fact, is simply about managing those objects that live in the subset of the world we're reproducing in our software. You can create, use, reuse, and delete objects as you please.

According to the *Data Model* chapter on the official Python documentation (`https://docs.python.org/3/reference/datamodel.html`):

"Objects are Python's abstraction for data. All data in a Python program is represented by objects or by relations between objects."

We will take a closer look at Python objects in *Chapter 6*, *OOP, Decorators, and Iterators*. For now, all we need to know is that every object in Python has an **ID** (or identity), a **type**, and a **value**.

Object-Oriented Programming (**OOP**) is just one of many programming paradigms. In Python, we can write code using a functional or imperative style, as well as object-oriented. However, as we previously stated, everything in Python is an object, therefore we employ them all the time, regardless of the chosen coding style.

Once created, the ID of an object never changes. It is a unique identifier for it, and it is used behind the scenes by Python to retrieve the object when we want to use it. The type also never changes. The type states what operations are supported by the object and the possible values that can be assigned to it. We will see Python's most important data types in *Chapter 2*, *Built-In Data Types*. The value of some objects can change. Such objects are said to be **mutable**. If the value cannot be changed, the object is said to be **immutable**.

How, then, do we use an object? We give it a name, of course! When you give an object a name, then you can use the name to retrieve the object and use it. In a more generic sense, objects, such as numbers, strings (text), and collections, are associated with a name. In other languages, the name is normally called a *variable*. You can see the variable as being like a box, which you can use to hold data.

Objects represent data. It is stored in databases or sent over network connections. It is what you see when you open any web page, or work on a document. Computer programs manipulate that data to perform all sorts of actions. They regulate its flow, evaluate conditions, react to events, and much more.

To do all this, we need a language. That is what Python is for. Python is the language we will use together throughout this book to instruct the computer to do something for us.

Enter the Python

Python is the marvelous creation of Guido Van Rossum, a Dutch computer scientist and mathematician who decided to gift the world with a project he was playing around with over Christmas 1989. The language appeared to the public somewhere around 1991, and since then has evolved to be one of the leading programming languages used worldwide today.

We (the authors) started programming when we were both very young. Fabrizio started at the age of 7, on a Commodore VIC-20, which was later replaced by its bigger brother, the Commodore 64. The language it used was **BASIC**. Heinrich started when he learned Pascal in high school. Between us, we've programmed in Pascal, Assembly, C, C++, Java, JavaScript, Visual Basic, PHP, ASP, ASP .NET, C#, and plenty of others we can't even remember; only when we landed on Python did we finally get the feeling that you go through when you find the right couch in the shop, when all of your body is yelling: *Buy this one! This one is perfect!*

It took us about a day to become accustomed to it. Its syntax is a bit different from what we were used to, but after getting past that initial feeling of discomfort (like having new shoes), we both just fell in love with it. Deeply. Let us see why.

About Python

Before we get into the gory details, let us get a sense of why someone would want to use Python. It embodies the following qualities.

Portability

Python runs everywhere, and porting a program from Linux to Windows or Mac is usually just a matter of fixing paths and settings. Python is designed for portability, and it takes care of specific **operating system** (**OS**) quirks behind interfaces that shield you from the pain of having to write code tailored to a specific platform.

Coherence

Python is extremely logical and coherent. You can see it was designed by a brilliant computer scientist. Most of the time, you can just guess what a method is called if you do not know it.

You may not realize how important this is right now, especially if you are not that experienced as a programmer, but this is a major feature. It means less clutter in your head, as well as less skimming through the documentation, and less need for mappings in your brain when you code.

Developer productivity

According to Mark Lutz (*Learning Python, 5th Edition, O'Reilly Media*), a Python program is typically one-fifth to one-third the size of equivalent Java or C++ code. This means the job gets done faster. And faster is good. Faster means being able to respond more quickly to the market. Less code not only means less code to write, but also less code to read (and professional coders read much more than they write), maintain, debug, and refactor.

Another important aspect is that Python runs without the need for lengthy and time-consuming compilation and linkage steps, so there is no need to wait to see the results of your work.

An extensive library

Python has an incredibly extensive standard library (it is said to come with *batteries included*). If that wasn't enough, the Python international community maintains a body of third-party libraries, tailored to specific needs, which you can access freely at the **Python Package Index** (**PyPI**). When you code in Python and realize that a certain feature is required, in most cases, there is at least one library where that feature has already been implemented.

Software quality

Python is heavily focused on readability, coherence, and quality. The language's uniformity allows high readability, and this is crucial nowadays, as coding is more of a collective effort than a solo endeavor. Another important aspect of Python is its intrinsic multiparadigm nature. You can use it as a scripting language, but you can also employ object-oriented, imperative, and functional programming styles—it is extremely versatile.

Software integration

Another important aspect is that Python can be extended and integrated with many other languages, which means that even when a company is using a different language as their mainstream tool, Python can come in and act as a gluing agent between complex applications that need to talk to each other in some way. This is more of an advanced topic, but in the real world, this feature is important.

Data science

Python is among the most popular (if not **the** most popular) languages used in the fields of data science, machine learning, and artificial intelligence today. Knowledge of Python is therefore almost essential for those who want to have a career in these fields.

Satisfaction and enjoyment

Last, but by no means least, there is the fun of it! Working with Python is fun; we can code for eight hours and leave the office happy and satisfied, unaffected by the struggle other coders have to endure because they use languages that do not provide them with the same amount of well-designed data structures and constructs. Python makes coding fun, no doubt about it, and fun promotes motivation and productivity.

These are the major reasons why we would recommend Python to everyone. Of course, there are many other technical and advanced features that we could have mentioned, but they do not really pertain to an introductory section like this one. They will come up naturally, chapter after chapter, as we learn about Python in greater detail.

Now, let's look at what the potential limitations of Python are.

What are the drawbacks?

Aside from personal preferences, the primary drawback of Python lies in its execution speed. Typically, Python is slower than its compiled siblings. The standard implementation of Python produces, when you run an application, a compiled version of the source code called byte code (with the extension `.pyc`), which is then run by the Python interpreter. The advantage of this approach is portability, which we pay for with increased runtimes because Python is not compiled down to the machine level, as other languages are.

Despite this, Python speed is rarely a problem today, hence its wide use regardless of this downside. What happens is that, in real life, hardware cost is no longer a problem, and usually you can gain speed by parallelizing tasks. Moreover, many programs spend a great proportion of the time waiting for I/O operations to complete; therefore, the raw execution speed is often a secondary factor to the overall performance.

It is worth noting that Python's core developers have put great effort into speeding up operations on the most common data structures in the last few years. This effort, in some cases very successful, has somewhat alleviated this issue.

In situations where speed really is crucial, one can switch to faster Python implementations, such as **PyPy**, which provides, on average, just over a four-fold speedup by implementing advanced compilation techniques (check `https://pypy.org/` for reference). It is also possible to write performance-critical parts of your code in faster languages, such as C or C++, and integrate that with your Python code. Libraries such as **pandas** and **NumPy** (which are commonly used for doing data science in Python) use such techniques.

There are a few different implementations of the Python language. In this book, we will use the reference implementation, known as CPython. You can find a list of other implementations at `https://www.python.org/download/alternatives/`.

If that is not convincing enough, you can always consider that Python has been used to drive the backend of services such as Spotify and Instagram, where performance is a concern. From this, it can be seen that Python has done its job perfectly well.

Who is using Python today?

Python is used in many different contexts, such as system programming, web and API programming, GUI applications, gaming and robotics, rapid prototyping, system integration, data science, database applications, real-time communication, and much more. Several prestigious universities have also adopted Python as their main language in computer science courses.

Here is a list of major companies and organizations that are known to use Python in their technology stack, product development, data analysis, or automation processes:

- Tech industry
    - Google: Uses Python for many tasks including backend services, data analysis, and artificial intelligence (AI)
    - Facebook: Utilizes Python for various purposes, including infrastructure management and operational automation
    - Instagram: Relies heavily on Python for its backend, making it one of the largest Django (a Python web framework) users
    - Spotify: Employs Python mainly for data analysis and backend services
    - Netflix: Uses Python for data analysis, operational automation, and security
- Financial sector
    - JP Morgan Chase: Uses Python for financial models, data analysis, and algorithmic trading
    - Goldman Sachs: Employs Python for various financial models and applications
    - Bloomberg: Uses Python for financial data analysis and its Bloomberg Terminal interface
- Technology and software
    - IBM: Utilizes Python for AI, machine learning, and cybersecurity
    - Intel: Uses Python for hardware testing and development processes
    - Dropbox: The desktop client is largely written in Python

- Space and research
    - NASA: Uses Python for various purposes, including data analysis and system integration
    - CERN: Employs Python for data processing and analysis in physics experiments
- Retail and e-Commerce
    - Amazon: Uses Python for data analysis, product recommendations, and operational automation
    - eBay: Utilizes Python for various backend services and data analysis
- Entertainment and media
    - Pixar: Uses Python for animation software and scripting in the animation process
    - Industrial Light & Magic (ILM): Employs Python for visual effects and image processing
- Education and learning platforms
    - Coursera: Utilizes Python for web development and backend services
    - Khan Academy: Uses Python for educational content delivery and backend services
- Government and non-profit
    - The United States Federal Government: Has various departments and agencies using Python for data analysis, cybersecurity, and automation
    - The Raspberry Pi Foundation: Uses Python as a primary programming language for educational purposes and projects

Setting up the environment

On our machines (MacBook Pro), this is the latest Python version:

```
>>> import sys
>>> print(sys.version)
3.12.2 (main, Feb 14 2024, 14:16:36) [Clang 15.0.0 (clang-1500.1.0.2.5)]
```

So, you can see that the version is 3.12.2, which was out on October 2, 2023. The preceding text is a little bit of Python code that was typed into a console. We will talk about this in a moment.

All the examples in this book will be run using Python 3.12. If you wish to follow the examples and download the source code for this book, please make sure you are using the same version.

Installing Python

The process of installing Python on your computer depends on the operating system you have. First of all, Python is fully integrated and, most likely, already installed in almost every Linux distribution. If you have a recent version of macOS, it is likely that Python 3 is already there as well, whereas if you are using Windows, you probably need to install it.

Regardless of Python being already installed in your system, you will need to make sure that you have version 3.12 installed.

To check if you have Python already installed on your system, try typing `python --version` or `python3 --version` in a command prompt (more on this later).

The place you want to start is the official Python website: `https://www.python.org`. This website hosts the official Python documentation and many other resources that you will find very useful.

Useful installation resources

The Python website hosts useful information regarding the installation of Python on various operating systems. Please refer to the relevant page for your operating system.

Windows and macOS:

- `https://docs.python.org/3/using/windows.html`
- `https://docs.python.org/3/using/mac.html`

For Linux, please refer to the following links:

- `https://docs.python.org/3/using/unix.html`
- `https://ubuntuhandbook.org/index.php/2023/05/install-python-3-12-ubuntu/`

Installing Python on Windows

As an example, this is the procedure to install Python on Windows. Head to `https://www.python.org/downloads/` and download the appropriate installer according to the CPU of your computer.

Once you have it, you can double-click on it in order to start the installation.

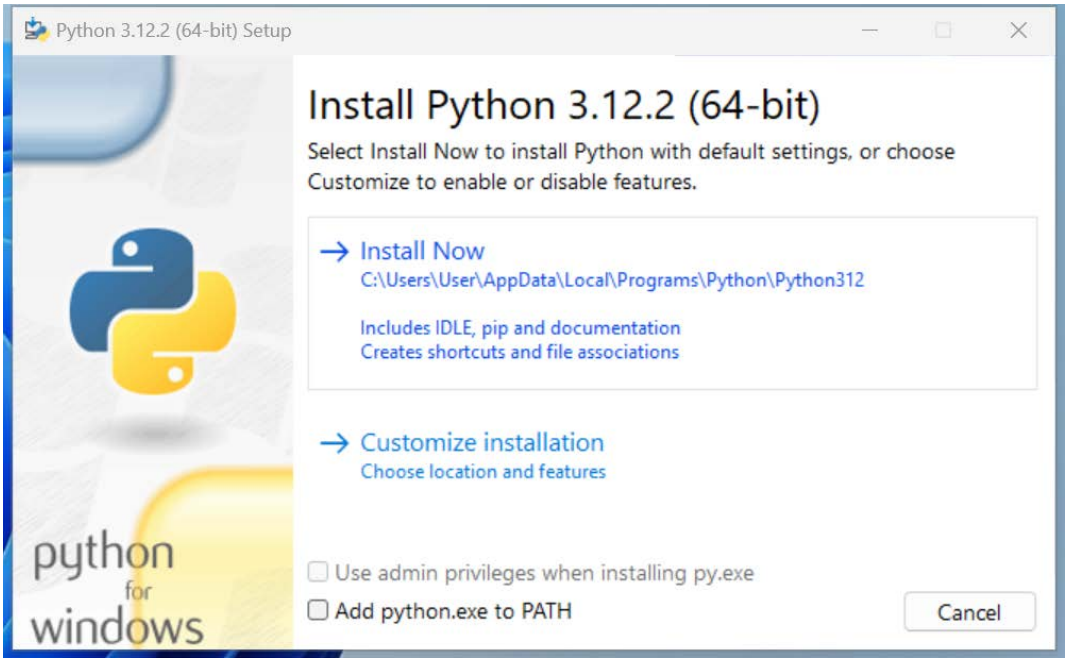

Figure 1.1: Starting the installation process on Windows

We recommend choosing the default install, and NOT ticking the **Add python.exe to PATH** option to prevent clashes with other versions of Python that might be installed on your machine, potentially by other users.

For a more comprehensive set of guidelines, please refer to the link indicated in the previous paragraph.

Once you click on **Install Now**, the installation procedure will begin.

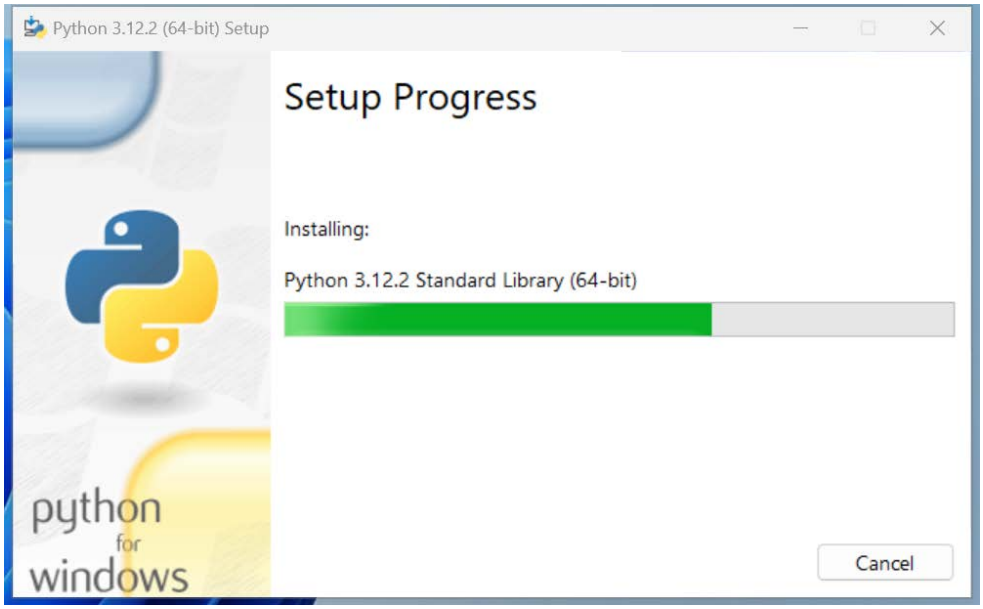

Figure 1.2: Installation in progress

Once the installation is complete, you will land on the final screen.

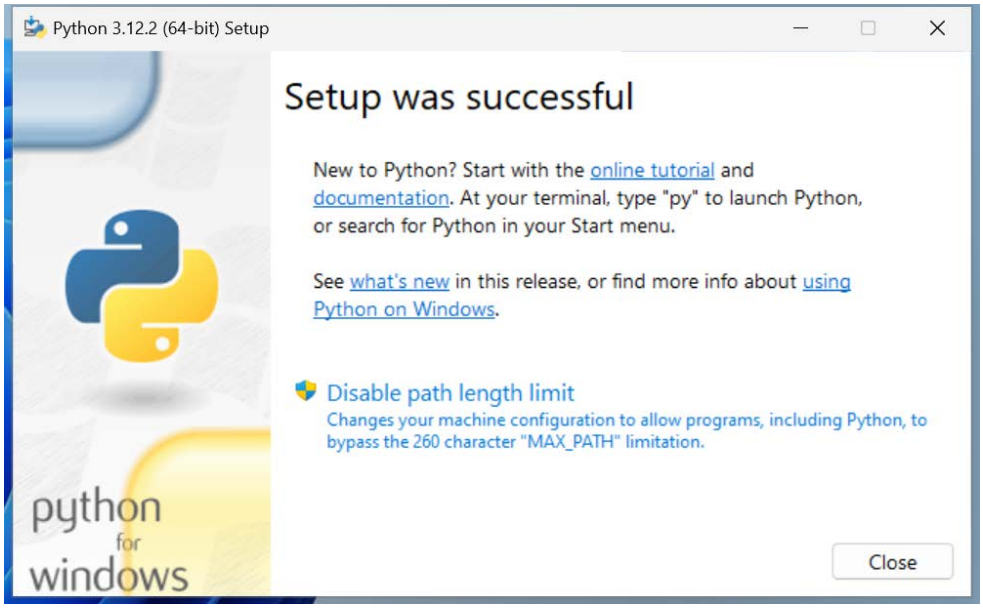

Figure 1.3: Installation complete

Click on **Close** to finish the installation.

Now that Python is installed on your system, open a command prompt and run the **Python interactive shell** by typing `py`. This command will select the latest version of Python installed on your machine. At the time of writing, 3.12 is the latest available version of Python. If you have a more recent version installed, you can specify the version with the command `py -3.12`.

To open the command prompt in Windows, go to the **Start** menu and type `cmd` in the search box to start your terminal up. Alternatively, you can also use Powershell.

Installing Python on macOS

On macOS, the installation procedure is similar to that of Windows. Once you have downloaded the appropriate installer for your machine, complete the installation steps, and then start a terminal by going to **Applications > Utilities > Terminal**. Alternatively, you can install it through Homebrew.

Once in the terminal window, you can type `python`. If that launches the wrong version, you can try and specify the version with either `python3` or `python3.12`.

Installing Python on Linux

The process of installing Python on Linux is normally a bit more complex than that for Windows or macOS. The best course of action, if you are on a Linux machine, is to search for the most up-to-date set of steps for your distribution online. These will likely be quite different from one distribution to another, so it is difficult to give an example that would be relevant for everyone. Please refer to the link in the *Useful installation resources* section for guidance.

The Python console

We will use the term **console** interchangeably to indicate the Linux console, the Windows Command Prompt or Powershell, and the macOS Terminal. We will also indicate the command-line prompt with the default Linux format, like this:

```
$ sudo apt-get update
```

If you are not familiar with that, please take some time to learn the basics of how a console works. In a nutshell, after the `$` sign, you will type your instructions. Pay attention to capitalization and spaces, as they are very important.

Whatever console you open, type `python` at the prompt (`py` on Windows) and make sure the Python interactive shell appears. Type `exit()` to quit. Keep in mind that you may have to specify `python3` or `python3.12` if your OS comes with other Python versions preinstalled.

We often refer to the Python interactive shell simply as the **Python console**.

This is roughly what you should see when you run Python (some details will change according to the version and OS):

```
$ python
Python 3.12.2 (main, Feb 14 2024, 14:16:36)
[Clang 15.0.0 (clang-1500.1.0.2.5)] on darwin
Type "help", "copyright", "credits" or "license" for more information.
>>>
```

Now that Python is set up and you can run it, it is time to make sure you have the other tool that will be indispensable to follow the examples in the book: a virtual environment.

About virtual environments

When working with Python, it is very common to use virtual environments. Let us see what they are and why we need them by means of a simple example.

You install Python on your system, and you start working on a website for client X. You create a project folder and start coding. Along the way, you also install some libraries, for example, the Django framework. Let us say the Django version you installed for Project X is 4.2.

Now, your website is so good that you get another client, Y. She wants you to build another website, so you start Project Y and, along the way, you need to install Django again. The only issue is that now the Django version is 5.0 and you cannot install it on your system because this would replace the version you installed for Project X. You do not want to risk introducing incompatibility issues, so you have two choices: either you stick with the version you have currently on your machine, or you upgrade it and make sure the first project is still fully working correctly with the new version.

Let us be honest; neither of these options is very appealing, right? Definitely not. But there is a solution: virtual environments!

Virtual environments are isolated Python environments, each of which is a folder that contains all the necessary executables to use the packages that a Python project would need (think of packages as libraries for the time being).

So, you create a virtual environment for Project X, install all the dependencies, and then you create a virtual environment for Project Y, and install all its dependencies without the slightest worry because every library you install ends up within the boundaries of the appropriate virtual environment. In our example, Project X will hold Django 4.2, while Project Y will hold Django 5.0.

It is of great importance that you never install libraries directly at the system level. Linux, for example, relies on Python for many different tasks and operations, and if you fiddle with the system installation of Python, you risk compromising the integrity of the entire system. So, take this as a rule: always create a virtual environment when you start a new project.

When it comes to creating a virtual environment on your system, there are a few different methods to carry this out. Since Python 3.5, the suggested way to create a virtual environment is to use the `venv` module. You can look it up on the official documentation page (`https://docs.python.org/3/library/venv.html`) for further information.

If you are using a Debian-based distribution of Linux, for example, you will need to install the `venv` module before you can use it:

```
$ sudo apt-get install python3.12-venv
```

Another common way of creating virtual environments is to use the `virtualenv` third-party Python package. You can find it on its official website: `https://virtualenv.pypa.io`.

In this book, we will use the recommended technique, which leverages the `venv` module from the Python standard library.

Your first virtual environment

It is very easy to create a virtual environment, but depending on how your system is configured and which Python version you want the virtual environment to run on, you need to run the command properly. Another thing you will need to do when you want to work with it is to activate it. Activating virtual environments produces some path juggling behind the scenes so that when you call the Python interpreter from that shell, it will come from within the virtual environment, instead of the system. We will show you a full example on macOS and Windows (on Linux, it will be very similar to that of macOS). We will:

1. Open a terminal and change into the folder (directory) we use as root for our projects (our folder is `code`). We are going to create a new folder called `my-project` and change into it.
2. Create a virtual environment called `lpp4ed`.
3. After creating the virtual environment, we will activate it. The methods are slightly different between Linux, macOS, and Windows.
4. Then, we will make sure that we are running the desired Python version (3.12.X) by running the Python interactive shell.
5. Finally, we will deactivate the virtual environment.

Some developers prefer to call all virtual environments with the same name (for example, `.venv`). This way, they can configure tools and run scripts against any virtual environment by just knowing their location. The dot in `.venv` is there because in Linux/macOS, prepending a name with a dot makes that file or folder "invisible."

These steps are all you need to start a project.

We are going to start with an example on macOS (note that you might get a slightly different result, according to your OS, Python version, and so on). In this listing, lines that start with a hash, #, are comments, spaces have been introduced for readability, and an arrow, ➔, indicates where the line has wrapped around due to lack of space:

```
fab@m1:~/code$ mkdir my-project  # step 1
fab@m1:~/code$ cd my-project

fab@m1:~/code/my-project$ which python3.12  # check system python
/usr/bin/python3.12  # <-- system python3.12

fab@m1:~/code/my-project$ python3.12 -m venv lpp4ed  # step 2
fab@m1:~/code/my-project$ source ./lpp4ed/bin/activate  # step 3

# check python again: now using the virtual environment's one
(lpp4ed) fab@m1:~/code/my-project$ which python
/Users/fab/code/my-project/lpp4ed/bin/python

(lpp4ed) fab@m1:~/code/my-project$ python  # step 4
Python 3.12.2 (main, Feb 14 2024, 14:16:36)
➔ [Clang 15.0.0 (clang-1500.1.0.2.5)] on darwin
```

```
Type "help", "copyright", "credits" or "license" for more information.
>>> exit()

(lpp4ed) fab@m1:~/code/my-project$ deactivate  # step 5
fab@m1:~/code/my-project$
```

Each step has been marked with a comment, so you should be able to follow along quite easily.

Something to notice here is that to activate the virtual environment, we need to run the `lpp4ed/bin/activate` script, which needs to be sourced. When a script is *sourced*, it means that it is executed in the current shell, and its effects last after the execution. This is very important. Also notice how the prompt changes after we activate the virtual environment, showing its name on the left (and how it disappears when we deactivate it).

On a Windows 11 PowerShell, the steps are as follows:

```
PS C:\Users\H\Code> mkdir my-project  # step 1
PS C:\Users\H\Code> cd .\my-project\

# check installed python versions
PS C:\Users\H\Code\my-project> py --list-paths
 -V:3.12 *
→ C:\Users\H\AppData\Local\Programs\Python\Python312\python.exe

PS C:\Users\H\Code\my-project> py -3.12 -m venv lpp4ed  # step 2
PS C:\Users\H\Code\my-project> .\lpp4ed\Scripts\activate  # step 3

# check python versions again: now using the virtual environment's
(lpp4ed) PS C:\Users\H\Code\my-project> py --list-paths
  *
→ C:\Users\H\Code\my-project\lpp4ed\Scripts\python.exe
 -V:3.12
→ C:\Users\H\AppData\Local\Programs\Python\Python312\python.exe

(lpp4ed) PS C:\Users\H\Code\my-project> python  # step 4
Python 3.12.2 (tags/v3.12.2:6abddd9, Feb  6 2024, 21:26:36)
→ [MSC v.1937 64 bit (AMD64)] on win32
Type "help", "copyright", "credits" or "license" for more
→ information.
```

```
>>> exit()

(lpp4ed) PS C:\Users\H\Code\my-project> deactivate  # step 5
PS C:\Users\H\Code\my-project>
```

Notice how, on Windows, after activating the virtual environment, you can either use the `py` command or, more directly, `python`.

At this point, you should be able to create and activate a virtual environment. Please try and create another one on your own. Get acquainted with this procedure—it is something that you will always be doing: *we never work system-wide with Python*, remember? Virtual environments are extremely important.

The source code for the book contains a dedicated folder for each chapter. When the code shown in the chapter requires third-party libraries to be installed, we will include a `requirements.txt` file (or an equivalent `requirements` folder with more than one text file inside) that you can use to install the libraries required to run that code. We suggest that when experimenting with the code for a chapter, you create a dedicated virtual environment for that chapter. This way, you will be able to get some practice in the creation of virtual environments, and the installation of third-party libraries.

Installing third-party libraries

In order to install third-party libraries, we need to use the Python Package Installer, known as **pip**. Chances are that it is already available to you within your virtual environment, but if not, you can learn all about it on its documentation page: `https://pip.pypa.io`.

The following example shows how to create a virtual environment and install a couple of third-party libraries taken from a requirements file:

```
fab@m1:~/code$ mkdir my-project
fab@m1:~/code$ cd my-project
fab@m1:~/code/my-project$ python3.12 -m venv lpp4ed
fab@m1:~/code/my-project$ source ./lpp4ed/bin/activate
(lpp4ed) fab@m1:~/code/my-project$ cat requirements.txt
django==5.0.3
requests==2.31.0
# the following instruction shows how to use pip to install
```

```
# requirements from a file
(lpp4ed) fab@m1:~/code/my-project$ pip install -r requirements.txt
Collecting django==5.0.3 (from -r requirements.txt (line 1))
  Using cached Django-5.0.3-py3-none-any.whl.metadata (4.2 kB)
Collecting requests==2.31.0 (from -r requirements.txt (line 2))
  Using cached requests-2.31.0-py3-none-any.whl.metadata (4.6 kB)
  ... more collecting omitted ...
Installing collected packages: ..., requests, django
Successfully installed ... django-5.0.3 requests-2.31.0
(lpp4ed) fab@m1:~/code/my-project$
```

As you can see at the bottom of the listing, `pip` has installed both libraries that are in the requirements file, plus a few more. This happened because both `django` and `requests` have their own list of third-party libraries that they depend upon, and therefore pip will install them automatically for us.

Using a `requirements.txt` file is just one of the many ways of installing third-party libraries in Python. You can also just specify the names of the packages you want to install directly, for example, `pip install django`.

You can find more information in the pip user guide: `https://pip.pypa.io/en/stable/user_guide/`.

Now, with the scaffolding out of the way, we are ready to talk a bit more about Python and how it can be used. Before we do that, though, allow us to say a few words about the console.

The console

In this era of GUIs and touchscreen devices, it may seem a little ridiculous to have to resort to a tool such as the console, when everything is just about one click away.

But the truth is every time you remove your hand from the keyboard to grab your mouse and move the cursor over to the spot you want to click on, you're losing time. Getting things done with the console, counter-intuitive though it may at first seem, results in higher productivity and speed. Believe us, we know—you will have to trust us on this.

Speed and productivity are important, and even though we have nothing against the mouse, being fluent with the console is very good for another reason: when you develop code that ends up on some server, the console might be the only available tool to access the code on that server. If you make friends with it, you will never get lost when it is of utmost importance that you do not (typically, when the website is down, and you have to investigate very quickly what has happened).

If you are still not convinced, please give us the benefit of the doubt and give it a try. It is easier than you think, and you will not regret it. There is nothing more pitiful than a good developer who gets lost within an SSH connection to a server because they are used to their own custom set of tools, and only to that.

Now, let us get back to Python.

How to run a Python program

There are a few different ways in which you can run a Python program.

Running Python scripts

Python can be used as a scripting language; in fact, it always proves itself very useful. Scripts are files (usually of small dimensions) that you normally execute to do something like a task. Many developers end up having an arsenal of tools that they use when they need to perform a task. For example, you can have scripts to parse data in a format and render it into another one, or you can use a script to work with files and folders; you can create or modify configuration files—technically, there is not much that cannot be done in a script.

It is rather common to have scripts running at a precise time on a server. For example, if your website database needs cleaning every 24 hours (for example, to regularly clean up expired user sessions), you could set up a Cron job that fires your script at 1:00 A.M. every day.

According to Wikipedia, the software utility Cron is a time-based job scheduler in Unix-like computer operating systems. People who set up and maintain software environments use Cron (or a similar technology) to schedule jobs (commands or shell scripts) to run periodically at fixed times, dates, or intervals.

We have Python scripts to do all the menial tasks that would take us minutes or more to do manually, and at some point, we decided to automate.

Running the Python interactive shell

Another way of running Python is by calling the interactive shell. This is something we saw when we typed `python` in the command line of our console.

So, open up a console, activate your virtual environment (which by now should be second nature to you, right?), and type `python`. You will be presented with a few lines that should look something like this:

```
(lpp4ed) fab@m1 ~/code/lpp4ed$ python
Python 3.12.2 (main, Feb 14 2024, 14:16:36)
[Clang 15.0.0 (clang-1500.1.0.2.5)] on darwin
Type "help", "copyright", "credits" or "license" for more
information.
>>>
```

Those `>>>` are the prompt of the shell. They tell you that Python is waiting for you to type something. If you type a simple instruction, something that fits in one line, that is all you will see. However, if you type something that requires more than one line of code, the shell will change the prompt to `...`, giving you a visual clue that you are typing a multiline statement (or anything that would require more than one line of code).

Go on, try it out; let us do some basic math:

```
>>> 3 + 7
10
>>> 10 / 4
2.5
>>> 2 ** 1024
179769313486231590772930519078902473361797697894230657273430081157
732675805500963132708477322407536021120113879871393357658789768814
416622492847430639474124377767893424865485276302219601246094119453
082952085005768838150682342462881473913110540827237163350510684586
298239947245938479716304835356329624224137216
```

The last operation is showing you something incredible. We raise `2` to the power of `1024`, and Python handles this task with no trouble at all. Try to do it in Java, C++, or C#. It will not work, unless you use special libraries to handle such big numbers.

We use the interactive shell every day. It is extremely useful to debug very quickly; for example, to check if a data structure supports an operation, or to inspect or run a piece of code. You will find that the interactive shell soon becomes one of your dearest friends on this journey you are embarking on.

Another solution, which comes in a much nicer graphic layout, is to use the **Integrated Development and Learning Environment (IDLE)**. It is quite a simple **Integrated Development Environment (IDE)**, which is intended mostly for beginners. It has a slightly larger set of capabilities than the bare interactive shell you get in the console, so you may want to explore it. It comes for free in the Windows and macOS Python installers, and you can easily install it on any other system. You can find more information about it on the Python website.

Guido Van Rossum named Python after the British comedy group Monty Python, so it is rumored that the name *IDLE* was chosen in honor of Eric Idle, one of Monty Python's founding members.

Running Python as a service

Apart from being run as a script, and within the boundaries of a shell, Python can be coded and run as an application. We will see examples throughout this book of this mode. We will look at it in more depth in a moment, when we talk about how Python code is organized and run.

Running Python as a GUI application

Python can also be used to create **Graphical User Interfaces (GUIs)**. There are several frameworks available, some of which are cross-platform, and some others that are platform-specific. A popular example of a GUI application library is **Tkinter**, which is an object-oriented layer that lives on top of `Tk` (Tkinter means Tk interface).

Tk is a GUI toolkit that takes desktop application development to a higher level than the conventional approach. It is the standard GUI for **Tool Command Language (Tcl)**, but also for many other dynamic languages, and it can produce rich native applications that run seamlessly on Windows, Linux, macOS, and more.

Tkinter comes bundled with Python; therefore, it gives the programmer easy access to the GUI world.

Other widely used GUI frameworks include:

- PyQT/PySide
- wxPython
- Kivy

Describing them in detail is outside the scope of this book, but you can find all the information you need on the Python website: `https://docs.python.org/3/faq/gui.html`.

Information can be found in the *What GUI toolkits exist for Python?* section. If GUIs are what you are looking for, remember to choose the one you want according to some basic principles. Make sure they:

- Offer all the features you may need to develop your project
- Run on all the platforms you may need to support
- Rely on a community that is as wide and active as possible
- Wrap graphic drivers/tools that you can easily install/access

How is Python code organized?

Let us talk a little bit about how Python code is organized. In this section, we will start to enter the proverbial rabbit hole and introduce more technical names and concepts.

Starting with the basics, how is Python code organized? Of course, you write your code into files. When you save a file with the extension `.py`, that file is said to be a Python **module**.

If you are on Windows or macOS, which typically hide file extensions from the user, we recommend that you change the configuration so that you can see the complete names of the files. This is not strictly a requirement, only a suggestion that may come in handy when discerning files from each other.

It would be impractical to save all the code that is required for software to work within one single file. That solution works for scripts, which are usually not longer than a few hundred lines (and often they are shorter than that).

A complete Python application can be made of hundreds of thousands of lines of code, so you will have to scatter it through different modules, which is better, but not good enough. It turns out that even like this, it would still be impractical to work with the code. So, Python gives you another structure, called a **package**, which allows you to group modules together.

A package is nothing more than a folder. In earlier versions of Python, a special file, `__init__.py`, was required to mark a directory as a package. This file does not need to contain any code, and even though its presence is not mandatory anymore, there are practical reasons why it is always a good idea to include it nonetheless.

As always, an example will make all this much clearer. We have created an illustration structure in our book project, and when we type in the console:

```
$ tree -v example
```

We get a tree representation of the contents of the `ch1/example` folder, which contains the code for the examples of this chapter. Here is what the structure of a simple application could look like:

```
example
├── core.py
├── run.py
└── util
    ├── __init__.py
    ├── db.py
    ├── maths.py
    └── network.py
```

You can see that within the root of this example, we have two modules, `core.py` and `run.py`, and one package, `util`. Within `core.py`, there may be the core logic of our application. On the other hand, within the `run.py` module, we can probably find the logic to start the application. Within the `util` package, we expect to find various utility tools and, in fact, we can guess that the modules there are named based on the types of tools they hold: `db.py` would hold tools to work with databases, `maths.py` would, of course, hold mathematical tools (maybe our application deals with financial data), and `network.py` would probably hold tools to send/receive data on networks.

As explained before, the `__init__.py` file is there just to tell Python that `util` is a package and not just a simple folder.

Had this software been organized within modules only, it would have been harder to infer its structure. We placed a *module-only* example in the `ch1/files_only` folder; see it for yourself:

```
$ tree -v files_only
```

This shows us a completely different picture:

```
files_only
├── core.py
```

```
├── db.py
├── maths.py
├── network.py
└── run.py
```

It is a little harder to guess what each module does, right? Now, consider that this is just a simple example, so you can guess how much harder it would be to understand a real application if we could not organize the code into packages and modules.

How do we use modules and packages?

When a developer is writing an application, it is likely that they will need to apply the same piece of logic in different parts of it. For example, when writing a parser for the data that comes from a form that a user can fill in a web page, the application will have to validate whether a certain field is holding a number or not. Regardless of how the logic for this kind of validation is written, it is likely that it will be needed for more than one field.

For example, in a poll application, where the user is asked many questions, it is likely that several of them will require a numeric answer. These might be:

- What is your age?
- How many pets do you own?
- How many children do you have?
- How many times have you been married?

It would be bad practice to copy/paste (or, said more formally, duplicate) the validation logic in every place where we expect a numeric answer. This would violate the **don't repeat yourself (DRY)** principle, which states that you should never repeat the same piece of code more than once in your application. Despite the DRY principle, we feel the need here to stress the importance of this principle: *you should never repeat the same piece of code more than once in your application*!

There are several reasons why repeating the same piece of logic can be bad, the most important ones being:

- There could be a bug in the logic, and therefore you would have to correct it in every copy.
- You may want to amend the way you carry out the validation, and again, you would have to change it in every copy.

- You may forget to fix or amend a piece of logic because you missed it when searching for all its occurrences. This would leave wrong or inconsistent behavior in your application.
- Your code would be longer than needed for no good reason.

Python is a wonderful language and provides you with all the tools you need to apply the coding best practices. For this example, we need to be able to reuse a piece of code. To do this effectively, we need to have a construct that will hold the code for us so that we can call that construct every time we need to repeat the logic inside it. That construct exists, and it is called a **function**.

We are not going too deep into the specifics here, so please just remember that a function is a block of organized, reusable code that is used to perform a task. Functions can assume many forms and names, according to what kind of environment they belong to, but for now, this is not important. Details will be seen once we are able to appreciate them, later in the book. Functions are the building blocks of modularity in your application, and they are almost indispensable. Unless you are writing a super-simple script, functions will be used all the time. Functions will be explored in *Chapter 4*, *Functions, the Building Blocks of Code*.

Python comes with a very extensive library, as mentioned a few pages ago. Now is a good time to define what a **library** is: a collection of functions and objects that provide functionalities to enrich the abilities of a language. For example, within Python's `math` library, a plethora of functions can be found, one of which is the `factorial` function, which calculates the factorial of a number.

In mathematics, the factorial of a non-negative integer number, N, denoted as N!, is defined as the product of all positive integers less than or equal to N. For example, the factorial of 5 is calculated as:

*N! = 1*2*3*4*5 = 120*

The factorial of 0 is 0! = 1, to respect the convention for an empty product.

So, if you want to use this function in your code, all you have to do is import it and call it with the right input values. Do not worry too much if input values and the concept of calling are not clear right now; please just concentrate on the import part. We use a library by importing specific components from it, which is then used for the intended purpose. In Python, to calculate 5!, we just need the following code:

```
>>> from math import factorial
>>> factorial(5)
120
```

Whatever we type in the shell, if it has a printable representation, will be printed in the console for us (in this case, the result of the function call: 120).

Let us go back to our example, the one with `core.py`, `run.py`, `util`, and so on. Here, the `util` package is our utility library. This is our custom utility belt that holds all those reusable tools (that is, functions), which we need in our application. Some of them will deal with databases (`db.py`), some with the network (`network.py`), and some will perform mathematical calculations (`maths.py`) that are outside the scope of Python's standard `math` library and, therefore, we must code them for ourselves.

We will see in detail how to import functions and use them in their dedicated chapter. Let us now talk about another important concept: *Python's execution model*.

Python's execution model

In this section, we would like to introduce you to some important concepts, such as scope, names, and namespaces. You can read all about Python's execution model in the official language reference (`https://docs.python.org/3/reference/executionmodel.html`), of course, but we would argue that it is quite technical and abstract, so let us give you a less formal explanation first.

Names and namespaces

Say you are looking for a book, so you go to the library and ask someone for it. They tell you something like *Second Floor, Section X, Row Three*. So, you go up the stairs, look for Section X, and so on. It would be very different to enter a library where all the books are piled together in random order in one big room. No floors, no sections, no rows, no order. Fetching a book would be extremely hard.

When we write code, we have the same issue: we have to try and organize it so that it will be easy for someone who has no prior knowledge about it to find what they are looking for. When software is structured correctly, it also promotes code reuse. Furthermore, disorganized software is more likely to contain scattered pieces of duplicated logic.

As a first example, let us take a book. We refer to a book by its title; in Python lingo, that would be a **name**. Python names are the closest abstraction to what other languages call variables. Names refer to objects and are introduced by **name-binding** operations. Let us see a quick example (again, notice that anything that follows a `#` is a comment):

```
>>> n = 3  # integer number
>>> address = "221b Baker Street, NW1 6XE, London"  # Sherlock Holmes'
address
>>> employee = {
...     'age': 45,
...     'role': 'CTO',
...     'SSN': 'AB1234567',
... }
>>> # let us print them
>>> n
3
>>> address
'221b Baker Street, NW1 6XE, London'
>>> employee
{'age': 45, 'role': 'CTO', 'SSN': 'AB1234567'}
>>> other_name
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
NameError: name 'other_name' is not defined
>>>
```

Remember that each Python object has an identity, a type, and a value. We defined three objects in the preceding code; let us now examine their types and values:

- An integer number `n` (type: `int`, value: `3`)
- A string `address` (type: `str`, value: Sherlock Holmes' address)
- A dictionary `employee` (type: `dict`, value: a dictionary object with three key/value pairs)

Fear not, we know we have not covered what a dictionary is. We will see, in *Chapter 2*, *Built-In Data Types*, that it is the king of Python data structures.

Have you noticed that the prompt changed from `>>>` to `...` when we typed in the definition of `employee`? That is because the definition spans multiple lines.

So, what are `n`, `address`, and `employee`? They are **names**, and they can be used to retrieve data from within our code. They need to be kept somewhere so that whenever we need to retrieve those objects, we can use their names to fetch them. We need some space to hold them, hence: **namespaces**!

A **namespace** is a mapping from names to objects. Examples are the set of built-in names (containing functions that are always accessible in any Python program), the global names in a module, and the local names in a function. Even the set of attributes of an object can be considered a namespace.

The beauty of namespaces is that they allow you to define and organize names with clarity, without overlapping or interference. For example, the namespace associated with the book we were looking for in the library could be used to import the book itself, like this:

```
from library.second_floor.section_x.row_three import book
```

We start from the `library` namespace, and by means of the dot (`.`) operator, we walk into that namespace. Within this namespace, we look for `second_floor` and, again, we walk into it with the `.` operator. We then walk into `section_x`, and finally, within the last namespace, `row_three`, we find the name we were looking for: `book`.

Walking through a namespace will be clearer when dealing with real code examples. For now, just keep in mind that namespaces are places where names are associated with objects.

There is another concept, closely related to that of a namespace, which we would like to mention briefly: **scope**.

Scopes

According to Python's documentation:

"A scope is a textual region of a Python program, where a namespace is directly accessible."

Directly accessible means that, when looking for an unqualified reference to a name, Python tries to find it in the namespace.

Scopes are determined statically, but at runtime, they are used dynamically. This means that by inspecting the source code, you can tell what the scope of an object is. There are four different scopes that Python makes accessible (not necessarily all of them are present at the same time, though):

- The **local** scope, which is the innermost one and contains the local names.
- The **enclosing** scope; that is, the scope of any enclosing function. It contains non-local names and non-global names.
- The **global** scope contains the global names.

- The **built-in** scope contains the built-in names. Python comes with a set of functions that you can use in an off-the-shelf fashion, such as `print`, `all`, `abs`, and so on. They live in the built-in scope.

The rule is the following: when we refer to a name, Python starts looking for it in the current namespace. If the name is not found, Python continues the search in the enclosing scope, and this continues until the built-in scope is searched. If a name has still not been found after searching the built-in scope, then Python raises a `NameError` **exception**, which basically means that the name has not been defined (as seen in the preceding example).

The order in which the namespaces are scanned when looking for a name is therefore **local**, **enclosing**, **global**, **built-in** (**LEGB**).

This is all theoretical, so let us see an example. To demonstrate local and enclosing namespaces, we will have to define a few functions. Do not worry if you are not familiar with their syntax for the moment—we will cover that in *Chapter 4*, *Functions, the Building Blocks of Code*. Just remember that in the following code, when you see `def`, it means we are defining a function:

```
# scopes1.py
# Local versus Global

# we define a function, called local
def local():
    age = 7
    print(age)

# we define age within the global scope
age = 5

# we call, or `execute` the function local
local()

print(age)
```

In the preceding example, we define the same name, `age`, in both the global and local scopes. When we execute this program with the following command (have you activated your virtual environment?):

```
$ python scopes1.py
```

We see two numbers printed on the console: 7 and 5.

What happens is that the Python interpreter parses the file, top to bottom. First, it finds a couple of comment lines, which are skipped, then it parses the definition of the function `local`. When called, this function will do two things: it will set a name for an object representing the number 7 and will print it. The Python interpreter keeps going, and it finds another name binding. This time, the binding happens in the global scope and the value is 5. On the next line, there is a call to the `local` function. At this point, Python executes the function, so this time, the binding `age = 7` happens in the local scope and is printed. Finally, there is a call to the `print` function, which is executed and will now print 5.

One particularly important thing to note is that the part of the code that belongs to the definition of the `local` function is indented by four spaces on the right. Python, in fact, defines scopes by indenting the code. You walk into a scope by indenting, and walk out of it by dedenting. Some coders use two spaces, others three, but the suggested number of spaces to use is four. It is a good measure to maximize readability. We will talk more about all the conventions you should embrace when writing Python code later.

In other languages, such as Java, C#, and C++, scopes are created by writing code within a pair of curly braces: { … }. Therefore, in Python, indenting code corresponds to opening a curly brace, while dedenting code corresponds to closing a curly brace.

What would happen if we removed that `age = 7` line? Remember the LEGB rule. Python would start looking for `age` in the local scope (function `local`), and, not finding it, it would go to the next enclosing scope. The next one, in this case, is the global one. Therefore, we would see the number 5 printed twice on the console. Let us see what the code would look like in this case:

```
# scopes2.py
# Local versus Global

def local():
    # age does not belong to the scope defined by the local
    # function so Python will keep looking into the next enclosing
    # scope. age is finally found in the global scope.
    print(age, 'printing from the local scope')

age = 5
print(age, 'printing from the global scope')
```

```
local()
```

Running `scopes2.py` will print this:

```
$ python scopes2.py
5 printing from the global scope
5 printing from the local scope
```

As expected, Python prints age the first time, then when the `local` function is called, age is not found in its scope, so Python looks for it following the LEGB chain until age is found in the global scope. Let us see an example with an extra layer, the enclosing scope:

```
# scopes3.py
# Local, Enclosing and Global

def enclosing_func():
    age = 13

    def local():
        # age does not belong to the scope defined by the local
        # function so Python will keep looking into the next
        # enclosing scope. This time age is found in the enclosing
        # scope
        print(age, 'printing from the local scope')

    # calling the function local
    local()

age = 5
print(age, 'printing from the global scope')

enclosing_func()
```

Running `scopes3.py` will print on the console:

```
$ python scopes3.py
5, 'printing from the global scope'
13, 'printing from the local scope'
```

As you can see, the `print` instruction from the `local` function is referring to `age` as before. `age` is still not defined within the function itself, so Python starts walking scopes following the LEGB order. This time, `age` is found in the *enclosing* scope.

Do not worry if this is still not perfectly clear for now. It will become clearer as we go through the examples in the book. The *Classes* section of the Python tutorial (`https://docs.python.org/3/tutorial/classes.html`) has an interesting paragraph about scopes and namespaces. Be sure you read it to gain a deeper understanding of the subject.

Guidelines for writing good code

Writing good code is not as easy as it seems. As we have already said, good code exhibits a long list of qualities that are difficult to combine. Writing good code is an art. Regardless of where on the path you will be happy to settle, there is something that you can embrace that will make your code instantly better: **PEP 8**.

A **Python Enhancement Proposal** (**PEP**) is a document that describes a newly proposed Python feature. PEPs are also used to document processes around Python language development and to provide guidelines and information. You can find an index of all PEPs at `https://www.python.org/dev/peps`.

PEP 8 is perhaps the most famous of all PEPs. It lays out a simple but effective set of guidelines to define Python aesthetics so that we write beautiful, idiomatic Python code. If you take just one suggestion out of this chapter, please let it be this: use PEP 8. Embrace it. You will thank us later.

Coding today is no longer a check-in/check-out business. Rather, it is more of a social effort. Several developers collaborate on a piece of code through tools such as Git and Mercurial, and the result is code that is produced by many different hands.

Git and Mercurial are two of the most popular distributed revision control systems in use today. They are essential tools designed to help teams of developers collaborate on the same software.

These days, more than ever, we need to have a consistent way of writing code, so that readability is maximized. When all developers of a company abide by PEP 8, it is not uncommon for any of them landing on a piece of code to think they wrote it themselves (it actually happens to Fabrizio all the time, because he quickly forgets any code he writes).

This has a tremendous advantage: when you read code that you could have written yourself, you read it easily. Without conventions, every coder would structure the code the way they like most, or simply the way they were taught or are used to, and this would mean having to interpret every line according to someone else's style. It would mean having to lose much more time just trying to understand it. Thanks to PEP 8, we can avoid this. We are such fans of it that, in our team, we will not sign off a code review if the code does not respect PEP 8. So, please take the time to study it; this is very important.

Python developers can leverage several different tools to automatically format their code, according to PEP 8 guidelines. Popular tools are *black* and *ruff*. There are also other tools, called linters, which check if the code is formatted correctly, and issue warnings to the developer with instructions on how to fix errors. Famous ones are *flake8* and *PyLint*. We encourage you to use these tools, as they simplify the task of coding well-formatted software.

In the examples in this book, we will try to respect PEP 8 as much as we can. Unfortunately, we do not have the luxury of 79 characters (which is the maximum line length suggested by PEP 8), and we will have to cut down on blank lines and other things, but we promise you we will try to lay out the code so that it is as readable as possible.

Python culture

Python has been adopted widely in the software industry. It is used by many different companies for different purposes, while also being an excellent education tool (it is excellent for that purpose due to its simplicity, making it easy to learn; it encourages good habits for writing readable code; it is platform-agnostic; and it supports modern object-oriented programming paradigms).

One of the reasons Python is so popular today is that the community around it is vast, vibrant, and full of brilliant people. Many events are organized all over the world, mostly either related to Python or to some of its most adopted web frameworks, such as Django.

Python's source is open, and very often so are the minds of those who embrace it. Check out the community page on the Python website for more information and get involved!

There is another aspect of Python, which revolves around the notion of being **Pythonic**. It has to do with the fact that Python allows you to use some idioms that are not found elsewhere, at least not in the same form or ease of use (it can feel claustrophobic when one has to code in a language that is not Python, at times).

Anyway, over the years, this concept of being Pythonic has emerged and, the way we understand it, it is something along the lines of *doing things the way they are supposed to be done in Python*.

To help you understand a little bit more about Python's culture and being Pythonic, we will show you the **Zen of Python**—a lovely *Easter egg* that is very popular. Open a Python console and type `import this`.

What follows is the result of that instruction:

```
>>> import this
The Zen of Python, by Tim Peters
Beautiful is better than ugly.
Explicit is better than implicit.
Simple is better than complex.
Complex is better than complicated.
Flat is better than nested.
Sparse is better than dense.
Readability counts.
Special cases aren't special enough to break the rules.
Although practicality beats purity.
Errors should never pass silently.
Unless explicitly silenced.
In the face of ambiguity, refuse the temptation to guess.
There should be one-- and preferably only one --obvious way to do it.
Although that way may not be obvious at first unless you're Dutch.
Now is better than never.
Although never is often better than *right* now.
If the implementation is hard to explain, it's a bad idea.
If the implementation is easy to explain, it may be a good idea.
Namespaces are one honking great idea -- let's do more of those!
```

There are two levels of reading here. One is to consider it as a set of guidelines that have been put together in a whimsical way. The other one is to keep it in mind and read it once in a while, trying to understand how it refers to something deeper: some Python characteristics that you will have to understand deeply in order to write Python the way it is supposed to be written. Start with the fun level, and then dig deeper. Always dig deeper.

A note on IDEs

Just a few words about IDEs. To follow the examples in this book, you do not need one; any decent text editor will do fine. If you want to have more advanced features, such as syntax coloring and auto-completion, you will have to get yourself an IDE. You can find a comprehensive list of open-source IDEs (just Google "Python IDEs") on the Python website.

Fabrizio uses Visual Studio Code, from Microsoft. It is free to use and it provides many features out of the box, which one can even expand by installing extensions.

After working for many years with several editors, including Sublime Text, this was the one that felt most productive to him.

Heinrich, on the other hand, is a hardcore Neovim user. Although it might have a steep learning curve, Neovim is a very powerful text editor that can also be extended with plugins. It also has the benefit of being compatible with its predecessor, Vim, which is installed in almost every system a software developer regularly works on.

Two important pieces of advice:

- Whatever IDE you decide to use, try to learn it well so that you can exploit its strengths, but *don't depend on it too much*. Practice working with Vim (or any other text editor) once in a while; learn to be able to do some work on any platform, with any set of tools.
- Whatever text editor/IDE you use, when it comes to writing Python, *indentation is four spaces*. Do not use tabs, do not mix them with spaces. Use four spaces, not two, not three, not five. Just use four. The whole world works like that, and you do not want to become an outcast because you were fond of the three-space layout.

A word about AI

In the last year or so, the world has witnessed the advent of AI. There are quite a few options on the market now, some of which provide tools for programmers.

The fact that there are instruments able to write pieces of code does not invalidate any of the reasons why one should learn a programming language. AI tools are far from being able to do what a person can do. They are not perfect, and at the time of writing, they are mostly used to help with repetitive and sometimes menial tasks.

Several IDEs can be integrated with technologies like GitHub Copilot (and the like). Visual Studio Code, Zed, IntelliJ IDEA, and PyCharm, all provide ways to enhance their capabilities with AI plugins. There are even some new IDEs that were designed specifically around AI features, such as Cursor.

While we do use such tools in our work, we feel it is crucial to stress how important it is for you to try and understand the code examples from this book on your own. Please try to work them out without help from an AI assistant, as that will be an integral part of your learning process.

Summary

In this chapter, we started exploring the world of programming and that of Python. We have barely scratched the surface, only touching upon concepts that will be discussed later on in the book in greater detail.

We talked about Python's main features, who is using it and for what, and the different ways in which we can write a Python program.

In the last part of the chapter, we flew over the fundamental notions of namespaces, and scopes. We also saw how Python code can be organized using modules and packages.

At a practical level, we learned how to install Python on our system and how to make sure we have the tools we need, such as `pip`; we also created and activated our first virtual environment. This will allow us to work in a self-contained environment without the risk of compromising the Python system installation.

Now you are ready to start this journey with us. All you need is enthusiasm, an activated virtual environment, this book, your fingers, and probably some coffee.

Try to follow the examples; we will keep them simple and short. If you put them to use, you will retain them much better than if you just read them.

In the next chapter, we will explore Python's rich set of built-in data types. There is much to cover, and much to learn!

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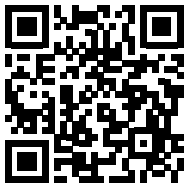
`https://discord.com/invite/uaKmaz7FEC`



2

Built-In Data Types

> *"Data! Data! Data!" he cried impatiently. "I can't make bricks without clay."*
>
> *—Sherlock Holmes, in The Adventure of the Copper Beeches*

Everything you do with a computer is managing data. Data comes in many different shapes and flavors. It is the music you listen to, the movies you stream, the PDFs you open. Even the source of the chapter you're reading at this very moment is just a file, which is data.

Data can be simple, whether it is an integer number to represent an age, or a complex structure, like an order placed on a website. It can be about a single object or about a collection of them. Data can even be about data—that is, **metadata**. This is data that describes the design of other data structures, or data that describes application data or its context. In Python, *objects are an abstraction for data*, and Python has an amazing variety of data structures that you can use to represent data or combine them to create your own custom data.

In this chapter, we are going to cover the following:

- Python objects' structures
- Mutability and immutability
- Built-in data types: numbers, strings, dates and times, sequences, collections, and mapping types
- The `collections` module, briefly
- Enumerations

Everything is an object

Before we delve into the specifics, we want you to be very clear about objects in Python, so let us talk a little bit more about them. *Everything in Python is an object*, and every object has an `identity` (`ID`), a `type`, and a `value`. But what really happens when you type an instruction like `age = 42` in a Python module?

If you go to `https://pythontutor.com/`, you can type that instruction into a text box and get its visual representation. Keep this website in mind; it is very useful to consolidate your understanding of what goes on behind the scenes.

So, what happens is that an **object** is created. It gets an `id`, the `type` is set to `int` (integer number), and the `value` to `42`. A name, `age`, is placed in the global namespace, pointing to that object. Therefore, whenever we are in the global namespace, after the execution of that line, we can retrieve that object by simply accessing it through its name: `age`.

If you were to move house, you would put all the knives, forks, and spoons in a box and label it *cutlery*. This is exactly the same concept. Here is a screenshot of what it may look like (you may have to tweak the settings to get the same view):

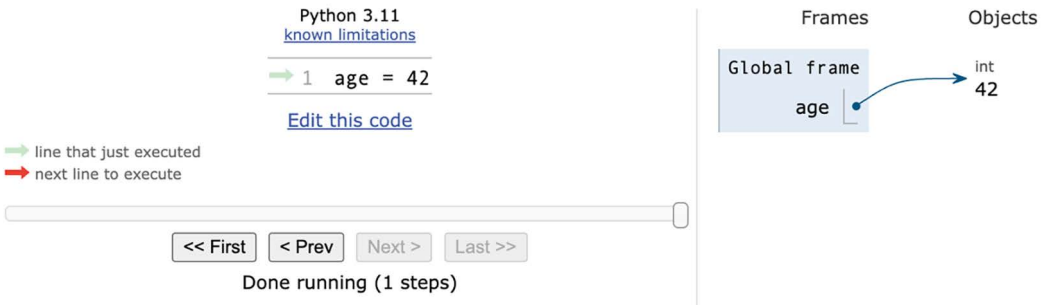


Figure 2.1 – A name pointing to an object

So, for the rest of this chapter, whenever you read something such as `name = some_value`, think of a name placed in the namespace that is tied to the scope in which the instruction was written, with a nice arrow pointing to an object that has an *id*, a *type*, and a *value*. There is a little bit more to say about this mechanism, but it is much easier to talk about it using an example, so we will come back to this later.

Mutability

The first fundamental distinction that Python makes about data is whether the value of an object can change. If the value can change, the object is called **mutable**, otherwise the object is called **immutable**.

It is important that you understand the distinction between mutable and immutable because it affects the code you write. Let us look at the following example:

```
>>> age = 42
>>> age
42
>>> age = 43  #A
>>> age
43
```

In the preceding code, on line `#A`, have we changed the value of `age`? Well, no. But now it is `43` (we hear you say...). Yes, it is `43`, but `42` was an integer number, of the type *int*, which is immutable. So, what happened is really that on the first line, `age` is a name that is set to point to an *int* object, whose value is `42`. When we type `age = 43`, what happens is that another *int* object is created, with the value `43` (also, the *id* will be different), and the name `age` is set to point to it. So, in fact, we did not change `42` to `43`—we just pointed the name `age` to a different location, which is the new *int* object whose value is `43`. Let us see the IDs of the objects:

```
>>> age = 42
>>> id(age)
4377553168
>>> age = 43
>>> id(age)
4377553200
```

Notice that we call the built-in `id()` function to print the IDs. As you can see, they are different, as expected. Bear in mind that `age` points to one object at a time: `42` first, then `43`—never together.

If you reproduce these examples on your computer, you will notice that the IDs you get will be different. This is of course expected, as they are generated randomly by Python and will be different every time.

Now, let us see the same example using a mutable object. For this example, we will use the built-in `set` type:

```
>>> numbers = set()
>>> id(numbers)
4368427136
>>> numbers
set()

>>> numbers.add(3)
>>> numbers.add(7)
>>> id(numbers)
4368427136
>>> numbers
{3, 7}
```

In this case, we set up an object, `numbers`, which represents a mathematical set. We can see its `id` being printed and the fact that it is empty (`set()`), right after creation. We then proceed to add two numbers to it: `3` and `7`. We print the `id` again (which shows it is the same object) and its value, which now shows it contains the two numbers. So the object's value has changed, but its `id` is still the same. This shows the typical behavior of a mutable object. We will explore sets in more detail later in this chapter.

Mutability is a very important concept. We will remind you about it throughout the rest of the chapter.

Numbers

Let us start by exploring Python's built-in data types for numbers. Python was designed by a man with a master's degree in mathematics and computer science, so it is only logical that it has extensive support for numbers.

Numbers are immutable objects.

Integers

Python integers have an unlimited range, subject only to the available virtual memory. This means that it doesn't really matter how big the number you want to store is—as long as it can fit in your computer's memory, Python will take care of it.

Integer numbers can be positive, negative, or 0 (zero). Their type is *int*. They support all the basic mathematical operations, as shown in the following example:

```
>>> a = 14
>>> b = 3
>>> a + b  # addition
17
>>> a - b  # subtraction
11
>>> a * b  # multiplication
42
>>> a / b  # true division
4.666666666666667
>>> a // b  # integer division
4
>>> a % b  # modulo operation (remainder of division)
2
>>> a ** b  # power operation
2744
```

The preceding code should be easy to understand. Just notice one important thing: Python has two division operators, one performs the so-called **true division** (`/`), which returns the quotient of the operands, and another one, the so-called **integer division** (`//`), which returns the *floored* quotient of the operands.

As historical information, in Python 2, the division operator `/` behaves differently than in Python 3.

Let us see how division behaves differently when we introduce negative numbers:

```
>>> 7 / 4  # true division
1.75
>>> 7 // 4  # integer division, truncation returns 1
1
>>> -7 / 4  # true division again, result is opposite of previous
-1.75
>>> -7 // 4  # integer div., result not the opposite of previous
-2
```

This is an interesting example. If you were expecting `-1` on the last line, don't feel bad, it is just the way Python works. Integer division in Python is *always rounded toward minus infinity*. If, instead of flooring, you want to truncate a number to an integer, you can use the built-in `int()` function, as shown in the following example:

```
>>> int(1.75)
1
>>> int(-1.75)
-1
```

Notice that the truncation is done toward 0 instead.

The `int()` function can also return integer numbers from string representation in a given base:

```
>>> int('10110', base=2)
22
```

It is worth noting that the power operator, `**`, also has a built-in function counterpart, `pow()`, shown in the example below:

```
>>> pow(10, 3)
1000
>>> 10 ** 3
1000
>>> pow(10, -3)
0.001
>>> 10 ** -3
0.001
```

There is also an operator to calculate the remainder of a division. It is called the **modulo operator**, and it is represented by a percentage symbol (`%`):

```
>>> 10 % 3  # remainder of the division 10 // 3
1
>>> 10 % 4  # remainder of the division 10 // 4
2
```

The `pow()` function allows a third argument to perform **modular exponentiation**.

The form with three arguments also accepts a negative exponent in the case where the base is relatively prime to the modulus. The result is the **modular multiplicative inverse** of the base (or a suitable power of that, when the exponent is negative, but not -1), modulo the third argument.

Here's an example:

```
>>> pow(123, 4)
228886641
>>> pow(123, 4, 100)
41  # notice: 228886641 % 100 == 41
>>> pow(37, -1, 43)  # modular inverse of 37 mod 43
7
>>> (7 * 37) % 43  # proof the above is correct
1
```

One nice feature introduced in Python 3.6 is the ability to add underscores within number literals (between digits or base specifiers, but not leading or trailing). The purpose is to help make some numbers more readable, such as `1_000_000_000`:

```
>>> n = 1_024
>>> n
1024
>>> hex_n = 0x_4_0_0  # 0x400 == 1024
>>> hex_n
1024
```

Booleans

Boolean algebra is that subset of algebra in which the values of the variables are the truth values, *true* and *false*. In Python, `True` and `False` are two keywords that are used to represent truth values. Booleans are a subclass of integers, so `True` and `False` behave respectively like `1` and `0`. The equivalent of the *int* type for Booleans is the *bool* type, which returns either `True` or `False`. Every built-in Python object has a value in the Boolean context, which means they evaluate to either `True` or `False` when fed to the `bool` function.

Boolean values can be combined in Boolean expressions using the logical operators `and`, `or`, and `not`. Let us see a simple example:

```
>>> int(True)  # True behaves like 1
1
>>> int(False)  # False behaves like 0
0
>>> bool(1)  # 1 evaluates to True in a Boolean context
True
>>> bool(-42)  # and so does every non-zero number
True
>>> bool(0)  # 0 evaluates to False
False
>>> # quick peek at the operators (and, or, not)
>>> not True
False
>>> not False
True
>>> True and True
True
>>> False or True
True
```

Booleans are most used in conditional programming, which we will discuss in detail in *Chapter 3, Conditionals and Iteration.*

You can see that `True` and `False` are subclasses of integers when you try to add them. Python upcasts them to integers and performs the addition:

```
>>> 1 + True
2
>>> False + 42
42
>>> 7 - True
6
```

Upcasting is a type conversion operation that goes from a subclass to its parent. In this example, `True` and `False`, which belong to a class derived from the integer class, are converted back to integers when needed. This topic is about inheritance and will be explained in detail in *Chapter 6*, *OOP, Decorators, and Iterators*.

Real numbers

Real numbers, or **floating point numbers**, are represented in Python according to the **IEEE 754** double-precision binary floating point format, which stores them in 64 bits of information divided into three sections: sign, exponent, and mantissa.

Quench your thirst for knowledge about this format on Wikipedia: `http://en.wikipedia.org/wiki/Double-precision_floating-point_format`.

Several programming languages offer two different formats: single and double precision. The former takes up 32 bits of memory, the latter 64. Python supports only the double format. Let us see a simple example:

```
>>> pi = 3.1415926536  # how many digits of PI can you remember?
>>> radius = 4.5
>>> area = pi * (radius ** 2)
>>> area
63.617251235400005
```

In the calculation of the area, we wrapped the `radius ** 2` within parentheses. Even though that wasn't necessary because the power operator has higher precedence than the multiplication one, we think the formula reads more easily like that. Moreover, should you get a slightly different result for the area, don't worry. It might depend on your OS, how Python was compiled, and so on. As long as the first few decimal digits are correct, you know it is the correct result.

The `sys.float_info` sequence holds information about how floating point numbers will behave on your system. This is an example of what you might see:

```
>>> import sys
>>> sys.float_info
sys.float_info(
    max=1.7976931348623157e+308, max_exp=1024, max_10_exp=308,
    min=2.2250738585072014e-308, min_exp=-1021, min_10_exp=-307,
    dig=15, mant_dig=53, epsilon=2.220446049250313e-16, radix=2,
    rounds=1
)
```

Let us make a few considerations here: we have 64 bits to represent floating point numbers. This means we can represent at most 2^{64} (that is *18,446,744,073,709,551,616*) distinct numbers. Take a look at the `max` and `epsilon` values for floating point numbers, and you will realize that it is impossible to represent them all. There is just not enough space, so they are approximated to the closest representable number. You probably think that only extremely big or extremely small numbers suffer from this issue. If so, the next example will surprise you:

```
>>> 0.3 - 0.1 * 3  # this should be 0!!!
-5.551115123125783e-17
```

What does this tell you? It tells you that double precision numbers suffer from approximation issues even when it comes to simple numbers like 0.1 or 0.3. Why is this important? It can be a big problem if you are handling prices, financial calculations, or any kind of data that requires precision. Don't worry, Python gives you the **Decimal** type, which doesn't suffer from these issues; we'll look at that in a moment.

Complex numbers

Python supports **complex numbers** out of the box. If you do not know what complex numbers are, they are numbers that can be expressed in the form *a + ib*, where *a* and *b* are real numbers, and *i* (or *j*, if you use the engineering notation) is the imaginary unit; that is, the square root of *-1*. *a* and *b* are called, respectively, the *real* and *imaginary* parts of the number.

It is perhaps unlikely that you will use them, but nevertheless, let us see a small example:

```
>>> c = 3.14 + 2.73j
>>> c = complex(3.14, 2.73)  # same as above
>>> c.real  # real part
```

```
3.14
>>> c.imag  # imaginary part
2.73
>>> c.conjugate()  # conjugate of A + Bj is A - Bj
(3.14-2.73j)
>>> c * 2  # multiplication is allowed
(6.28+5.46j)
>>> c ** 2  # power operation as well
(2.406700000000001+17.1444j)
>>> d = 1 + 1j  # addition and subtraction as well
>>> c - d
(2.14+1.73j)
```

Fractions and decimals

Let us finish the tour of the number department with a look at fractions and decimals. Fractions hold a rational numerator and denominator in their lowest forms. Let us see a quick example:

```
>>> from fractions import Fraction
>>> Fraction(10, 6)  # mad hatter?
Fraction(5, 3)  # notice it has been simplified
>>> Fraction(1, 3) + Fraction(2, 3)  # 1/3 + 2/3 == 3/3 == 1/1
Fraction(1, 1)
>>> f = Fraction(10, 6)
>>> f.numerator
5
>>> f.denominator
3
>>> f.as_integer_ratio()
(5, 3)
```

The `as_integer_ratio()` method has also been added to integers and Booleans. This is helpful, as it allows you to use it without needing to worry about what type of number is being worked with.

Other than passing the numerator and denominator, fractions can also be initialized by passing strings, decimals, floats, and of course fractions. Let us see an example with floats and strings:

```
>>> Fraction(0.125)
Fraction(1, 8)
>>> Fraction("3 / 7")
```

```
Fraction(3, 7)
>>> Fraction("-.250")
Fraction(-1, 4)
```

Although `Fraction` objects can be very useful at times, it is not that common to spot them in commercial software. Instead, it is much more common to see decimal numbers being used in all those contexts where precision is everything, for example, in scientific and financial calculations.

It is important to remember that arbitrary precision decimal numbers come at a price in terms of performance, of course. The amount of data to be stored for each number is greater than it is for fractions or floats. The way they are handled also requires the Python interpreter to work harder behind the scenes.

Let us see a quick example with decimal numbers:

```
>>> from decimal import Decimal as D  # rename for brevity
>>> D(3.14)  # pi, from float, so approximation issues
Decimal('3.140000000000000124344978758017532527446746826171875')
>>> D("3.14")  # pi, from a string, so no approximation issues
Decimal('3.14')
>>> D(0.1) * D(3) - D(0.3)  # from float, we still have the issue
Decimal('2.77555756156515654042363166 8E-17')
>>> D("0.1") * D(3) - D("0.3")  # from string, all perfect
Decimal('0.0')
>>> D("1.4").as_integer_ratio()  # 7/5 = 1.4 (isn't this cool?!)
(7, 5)
```

Notice that when we construct a decimal number from a float, it takes on all the approximation issues a float may come with. On the other hand, when we create a `decimal` from an `integer` or a `string` representation of a number, then the `decimal` will have no approximation issues, and therefore no quirky behavior. When it comes to currency or situations in which precision is of utmost importance, use decimals.

This concludes our introduction to built-in numeric types. Let us now look at sequences.

Immutable sequences

Let us explore immutable sequences: strings, tuples, and bytes.

Strings and bytes

Textual data in Python is handled with **str** objects, more commonly known as **strings**. They are immutable sequences of **Unicode code points**.

Unicode code points are the numbers assigned to each character in the Unicode standard, which is a universal character encoding scheme used to represent text in computers. The Unicode standard provides a unique number for every character, regardless of the platform, program, or language, thereby enabling the consistent representation and manipulation of text across different systems. Unicode covers a wide range of characters, including letters from the Latin alphabet, ideographs from Chinese, Japanese, and Korean writing systems, symbols, emojis, and more.

Unlike other languages, Python does not have a **char** type, so a single character is represented by a string of length 1.

Unicode should be used for the internals of any application. When it comes to storing textual data though, or sending it on the network, you will usually need to encode it, using an appropriate encoding for the medium you are using. The result of an encoding produces a **bytes** object, whose syntax and behavior are similar to that of strings. String literals are written in Python using single, double, or triple quotes (either single or double). If built with triple quotes, a string can span multiple lines. An example will clarify this:

```
>>> # 4 ways to make a string
>>> str1 = 'This is a string. We built it with single quotes.'
>>> str2 = "This is also a string, but built with double quotes."
>>> str3 = '''This is built using triple quotes,
... so it can span multiple lines.'''
>>> str4 = """This too
... is a multiline one
... built with triple double-quotes."""
>>> str4  #A
'This too\nis a multiline one\nbuilt with triple double-quotes.'
>>> print(str4)  #B
This too
is a multiline one
built with triple double-quotes.
```

In `#A` and `#B`, we print `str4`, first implicitly, and then explicitly, using the `print()` function. A good exercise would be to find out why they are different. Are you up to the challenge? (Hint: look up the `str()` and `repr()` functions.)

Strings, like any sequence, have a length. You can get this by calling the `len()` function:

```
>>> len(str1)
49
```

Python 3.9 has introduced two new methods that deal with the prefixes and suffixes of strings. Here's an example that explains the way they work:

```
>>> s = "Hello There"
>>> s.removeprefix("Hell")
'o There'
>>> s.removesuffix("here")
'Hello T'
>>> s.removeprefix("Ooops")
'Hello There'
```

The nice thing about them is shown by the last instruction: when we attempt to remove a prefix or suffix that is not there, the method simply returns a copy of the original string. Behind the scenes, these methods check if the string has a prefix or suffix that matches the argument of the call, and if that is the case, they remove it.

Encoding and decoding strings

Using the `encode/decode` methods, we can encode Unicode strings and decode bytes objects. **UTF-8** is a variable-length **character encoding**, capable of encoding all possible Unicode code points. It is the most widely used encoding for the web. Also notice that by adding the literal `b` in front of a string declaration, we are creating a `bytes` object:

```
>>> s = "This is üŋíc0de"  # unicode string: code points
>>> type(s)
<class 'str'>
>>> encoded_s = s.encode("utf-8")  # utf-8 encoded version of s
>>> encoded_s
b'This is \xc3\xbc\xc5\x8b\xc3\xadc0de'  # result: bytes object
>>> type(encoded_s)  # another way to verify it
<class 'bytes'>
>>> encoded_s.decode("utf-8")  # let us revert to the original
'This is üŋíc0de'
>>> bytes_obj = b"A bytes object"  # a bytes object
>>> type(bytes_obj)
<class 'bytes'>
```

Indexing and slicing strings

When manipulating sequences, it is very common to access them at one precise position (**indexing**) or to get a sub-sequence out of them (**slicing**). When dealing with immutable sequences, both operations are read-only.

While indexing comes in one form—zero-based access to any position within the sequence—slicing comes in different forms. When you get a slice of a sequence, you can specify the *start* and *stop* positions, along with the *step*. They are separated with a colon (`:`) like this: `my_sequence[start:stop:step]`. All the arguments are optional; `start` is inclusive, and `stop` is exclusive. It is probably better to see an example, rather than trying to explain them any further with words:

```
>>> s = "The trouble is you think you have time."
>>> s[0]  # indexing at position 0, which is the first char
'T'
>>> s[5]  # indexing at position 5, which is the sixth char
'r'
>>> s[:4]  # slicing, we specify only the stop position
'The '
>>> s[4:]  # slicing, we specify only the start position
'trouble is you think you have time.'
>>> s[2:14]  # slicing, both start and stop positions
'e trouble is'
>>> s[2:14:3]  # slicing, start, stop and step (every 3 chars)
'erb '
>>> s[:]  # quick way of making a copy
'The trouble is you think you have time.'
```

The last line is quite interesting. If you don't specify any of the parameters, Python will fill in the defaults for you. In this case, *start* will be the start of the string, *stop* will be the end of the string, and *step* will be the default: 1. This is an easy and quick way of obtaining a copy of the string `s` (the same value, but a different object). Can you think of a way to get the reversed copy of a string using slicing (do not look it up—find it for yourself)?

String formatting

One useful feature of strings is that they can be used as templates. This means that they can contain placeholders that can be replaced by arbitrary values using formatting operations. There are several ways of formatting a string. For the full list of possibilities, we encourage you to look up the documentation. Here are some common examples:

```
>>> greet_old = "Hello %s!"
>>> greet_old % 'Fabrizio'
'Hello Fabrizio!'
>>> greet_positional = "Hello {}!"
>>> greet_positional.format("Fabrizio")
'Hello Fabrizio!'
>>> greet_positional = "Hello {} {}!"
>>> greet_positional.format("Fabrizio", "Romano")
'Hello Fabrizio Romano!'
>>> greet_positional_idx = "This is {0}! {1} loves {0}!"
>>> greet_positional_idx.format("Python", "Heinrich")
'This is Python! Heinrich loves Python!'
>>> greet_positional_idx.format("Coffee", "Fab")
'This is Coffee! Fab loves Coffee!'
>>> keyword = "Hello, my name is {name} {last_name}"
>>> keyword.format(name="Fabrizio", last_name="Romano")
'Hello, my name is Fabrizio Romano'
```

In the previous example, you can see four different ways of formatting strings. The first one, which relies on the `%` operator, can lead to unexpected errors and should be used with care. A more modern way to format a string is by using the `format()` string method. You can see, from the different examples, that a pair of curly braces acts as a placeholder within the string. When we call `format()`, we feed it data that replaces the placeholders. We can specify indexes (and much more) within the curly braces, and even names, which implies we must call `format()` using keyword arguments instead of positional ones.

Notice how `greet_positional_idx` is rendered differently by feeding different data to the call to `format`.

One feature we want to show you was added to Python in version 3.6, and it is called **formatted string literals**. This feature is quite cool (and it is faster than using the `format()` method): strings are prefixed with `f`, and contain replacement fields surrounded by curly braces.

Replacement fields are expressions evaluated at runtime, and then formatted using the format protocol:

```
>>> name = "Fab"
>>> age = 48
>>> f"Hello! My name is {name} and I'm {age}"
"Hello! My name is Fab and I'm 48"
>>> from math import pi
>>> f"No arguing with {pi}, it's irrational..."
"No arguing with 3.141592653589793, it's irrational..."
```

An interesting addition to f-strings, which was introduced in Python 3.8, is the ability to add an equal sign specifier within the f-string clause; this causes the expression to expand to the text of the expression, an equal sign, then the representation of the evaluated expression. This is great for self-documenting and debugging purposes. Here's an example that shows the difference in behavior:

```
>>> user = "heinrich"
>>> password = "super-secret"
>>> f"Log in with: {user} and {password}"
'Log in with: heinrich and super-secret'
>>> f"Log in with: {user=} and {password=}"
"Log in with: user='heinrich' and password='super-secret'"
```

In version 3.12, the f-string syntactic formalization has been upgraded with a few features, which are outlined in PEP 701 (`https://peps.python.org/pep-0701/`). One of these features is quote reuse:

```
>>> languages = ["Python", "Javascript"]
>>> f"Two very popular languages: {", ".join(languages)}"
'Two very popular languages: Python, Javascript'
```

Notice how we have reused double quotes within the curly braces, and this hasn't broken our code. Here we are using the `join()` method of the string `","` to join together the strings from the `languages` list using a comma and a space. In previous versions of Python, we would have had to delimit the string inside the curly braces using single quotes: `', '`.

Another feature is the ability to write multiline expressions and comments, and also to use backslashes (\), which wasn't allowed before.

```
>>> f"Who knew f-strings could be so powerful? {"\N{shrug}"}"
'Who knew f-strings could be so powerful? 🤷'
```

Check out the official documentation to learn everything about string formatting and how powerful it can be.

Tuples

The last immutable sequence type we are going to look at here is the **tuple**. A tuple is a sequence of arbitrary Python objects. In a tuple declaration, items are separated by commas. Tuples are used everywhere in Python. They allow patterns that are quite hard to reproduce in other languages. Sometimes tuples are used without parentheses; for example, to set up multiple variables on one line, or to allow a function to return multiple objects (in several languages, it is common for functions to only be able to return one object), and in the Python console, tuples can be used implicitly to print multiple elements with one single instruction. We will see examples for all these cases:

```
>>> t = ()  # empty tuple
>>> type(t)
<class 'tuple'>
>>> one_element_tuple = (42, )  # you need the comma!
>>> three_elements_tuple = (1, 3, 5)  # braces are optional here
>>> a, b, c = 1, 2, 3  # tuple for multiple assignment
>>> a, b, c  # implicit tuple to print with one instruction
(1, 2, 3)
>>> 3 in three_elements_tuple  # membership test
True
```

We use the `in` operator to check whether a value is a member of a tuple. This membership operator can also be used with lists, strings, and dictionaries, and with collection and sequence objects, in general.

To create a tuple with one item, we need to put a comma after the item. The reason is that, without the comma, that item is wrapped in braces on its own, in what can be considered a redundant expression. Notice also that, on assignment, braces are optional, so `my_tuple = 1, 2, 3` is the same as `my_tuple = (1, 2, 3)`.

One thing that tuple assignment allows us to do is *one-line swaps*, with no need for a third temporary variable. Let us first see the traditional way of doing it:

```
>>> a, b = 1, 2
>>> c = a  # we need three lines and a temporary var c
>>> a = b
>>> b = c
>>> a, b  # a and b have been swapped
(2, 1)
```

Now let us see how we would do it in Python:

```
>>> a, b = 0, 1
>>> a, b = b, a  # this is the Pythonic way to do it
>>> a, b
(1, 0)
```

Look at the line that shows you the Pythonic way of swapping two values. Do you remember what we wrote in *Chapter 1*, *A Gentle Introduction to Python*? A Python program is typically one-fifth to one-third the size of equivalent Java or C++ code and features like one-line swaps contribute to this. Python is elegant, where elegance in this context also means economy.

Because they are immutable, tuples can be used as keys for dictionaries (we will see this shortly). To us, tuples are Python's built-in data that most closely represent a mathematical vector. This does not mean that this was the reason for which they were created, though. Tuples usually contain a heterogeneous sequence of elements while, on the other hand, lists are, most of the time, homogeneous. Moreover, tuples are normally accessed via unpacking or indexing, while lists are usually iterated over.

Mutable sequences

Mutable sequences differ from their immutable counterparts in that they can be changed after creation. There are two mutable sequence types in Python: **lists** and **bytearrays**.

Lists

Python lists are similar to tuples, but they do not have the restrictions of immutability. Lists are commonly used for storing collections of homogeneous objects, but there is nothing preventing you from storing heterogeneous collections as well. Lists can be created in many different ways. Let us see an example:

```
>>> []  # empty list
[]
>>> list()  # same as []
[]
>>> [1, 2, 3]  # as with tuples, items are comma separated
[1, 2, 3]
>>> [x + 5 for x in [2, 3, 4]]  # Python is magic
[7, 8, 9]
>>> list((1, 3, 5, 7, 9))  # list from a tuple
[1, 3, 5, 7, 9]
>>> list("hello")  # list from a string
['h', 'e', 'l', 'l', 'o']
```

In the previous example, we showed you how to create a list using various techniques. We would like you to take a good look at the line with the comment *Python is magic*, which we do not expect you to fully understand at this point—especially if you are unfamiliar with Python. That is called a **list comprehension**: a powerful functional feature of Python, which we will see in detail in *Chapter 5*, *Comprehensions and Generators*. We just wanted to spark your curiosity at this point.

Creating lists is good, but the real fun begins when we use them, so let us see the main methods they offer:

```
>>> a = [1, 2, 1, 3]
>>> a.append(13)  # we can append anything at the end
>>> a
[1, 2, 1, 3, 13]
>>> a.count(1)  # how many `1` are there in the list?
2
>>> a.extend([5, 7])  # extend the list by another (or sequence)
>>> a
[1, 2, 1, 3, 13, 5, 7]
>>> a.index(13)  # position of `13` in the list (0-based indexing)
```

```
4
>>> a.insert(0, 17)  # insert `17` at position 0
>>> a
[17, 1, 2, 1, 3, 13, 5, 7]
>>> a.pop()  # pop (remove and return) last element
7
>>> a.pop(3)  # pop element at position 3
1
>>> a
[17, 1, 2, 3, 13, 5]
>>> a.remove(17)  # remove `17` from the list
>>> a
[1, 2, 3, 13, 5]
>>> a.reverse()  # reverse the order of the elements in the list
>>> a
[5, 13, 3, 2, 1]
>>> a.sort()  # sort the list
>>> a
[1, 2, 3, 5, 13]
>>> a.clear()  # remove all elements from the list
>>> a
[]
```

The preceding code gives you a roundup of a list's main methods. We want to show you how powerful they are using the `extend()` method as an example. You can extend lists using any sequence type:

```
>>> a = list("hello")  # makes a list from a string
>>> a
['h', 'e', 'l', 'l', 'o']
>>> a.append(100)  # append 100, heterogeneous type
>>> a
['h', 'e', 'l', 'l', 'o', 100]
>>> a.extend((1, 2, 3))  # extend using tuple
>>> a
['h', 'e', 'l', 'l', 'o', 100, 1, 2, 3]
>>> a.extend('...')  # extend using string
>>> a
['h', 'e', 'l', 'l', 'o', 100, 1, 2, 3, '.', '.', '.']
```

Now, let us see some common operations you can do with lists:

```
>>> a = [1, 3, 5, 7]
>>> min(a)  # minimum value in the list
1
>>> max(a)  # maximum value in the list
7
>>> sum(a)  # sum of all values in the list
16
>>> from math import prod
>>> prod(a)  # product of all values in the list
105
>>> len(a)  # number of elements in the list
4
>>> b = [6, 7, 8]
>>> a + b  # `+` with list means concatenation
[1, 3, 5, 7, 6, 7, 8]
>>> a * 2  # `*` has also a special meaning
[1, 3, 5, 7, 1, 3, 5, 7]
```

Notice how easily we can perform the sum and the product of all values in a list. The `prod()` function, from the `math` module, is just one of the many additions introduced in Python 3.8. Even if you do not plan to use it that often, it is a good idea to check out the `math` module and be familiar with its functions, as they can be quite helpful.

The last two lines in the preceding code are also quite interesting, as they introduce us to a concept called **operator overloading**. In short, this means that operators, such as +, -, *, %, and so on, may represent different operations according to the context they are used in. It does not make any sense to sum two lists, right? Therefore, the + sign is used to concatenate them. Hence, the * sign is used to concatenate the list to itself a number of times specified by the right operand.

Now, let us take a step further and see something a little more interesting. We want to show you how powerful the `sorted` method can be and how easy it is in Python to achieve results that may require a great deal of effort in other languages:

```
>>> from operator import itemgetter
>>> a = [(5, 3), (1, 3), (1, 2), (2, -1), (4, 9)]
>>> sorted(a)
[(1, 2), (1, 3), (2, -1), (4, 9), (5, 3)]
```

```
>>> sorted(a, key=itemgetter(0))
[(1, 3), (1, 2), (2, -1), (4, 9), (5, 3)]
>>> sorted(a, key=itemgetter(0, 1))
[(1, 2), (1, 3), (2, -1), (4, 9), (5, 3)]
>>> sorted(a, key=itemgetter(1))
[(2, -1), (1, 2), (5, 3), (1, 3), (4, 9)]
>>> sorted(a, key=itemgetter(1), reverse=True)
[(4, 9), (5, 3), (1, 3), (1, 2), (2, -1)]
```

The preceding code deserves a little explanation. Note that, `a` is a list of tuples. This means each element in `a` is a tuple (a 2-tuple in this case). When we call `sorted(my_list)`, we get a sorted version of `my_list`. In this case, the sorting on a 2-tuple works by sorting them on the first item in the tuple, and on the second when the first one is the same. You can see this behavior in the result of `sorted(a)`, which yields `[(1, 2), (1, 3), ...]`. Python also gives us the ability to control which element(s) of the tuple the sorting must be run against. Notice that when we instruct the `sorted` function, to work on the first element of each tuple (with `key=itemgetter(0)`), the result is different: `[(1, 3), (1, 2), ...]`. The sorting is done only on the first element of each tuple (which is the one at position 0). If we want to replicate the default behavior of a simple `sorted(a)` call, we need to use `key=itemgetter(0, 1)`, which tells Python to sort first on the elements at position 0 within the tuples, and then on those at position 1. Compare the results and you will see that they match.

For completeness, we included an example of sorting only on the elements at position 1, and then again, with the same sorting but in reverse order. If you have ever seen sorting in other languages, you should be quite impressed at this moment.

The Python sorting algorithm is very powerful, and it was written by Tim Peters (the author of *The Zen of Python*). It is aptly named **Timsort**, and it is a blend between **merge** and **insertion sort** and has better time performance than most other algorithms used for mainstream programming languages. Timsort is a stable sorting algorithm, which means that when multiple records score the same in the comparison, their original order is preserved. We have seen this in the result of `sorted(a, key=itemgetter(0))`, which yielded `[(1, 3), (1, 2), ...]`, in which the order of those two tuples was preserved because they had the same value at position 0.

Bytearrays

To conclude our overview of mutable sequence types, let us spend a moment on the **bytearray** type. Bytearrays are the mutable version of bytes objects. They expose most of the usual methods of mutable sequences as well as most of the methods of the bytes type. Items in a bytearray are integers in the range [0, 256).

To represent intervals, we are going to use the standard notation for open/closed ranges. A square bracket on one end means that the value is included, while a round bracket means that it is excluded. The granularity is usually inferred by the type of the edge elements so, for example, the interval [3, 7] means all integers between 3 and 7, inclusive. On the other hand, (3, 7) means all integers between 3 and 7, exclusive (4, 5, and 6). Items in a bytearray type are integers between 0 and 256; 0 is included, 256 is not.

One reason that intervals are often expressed like this is to ease coding. If we break a range [a, b) into N consecutive ranges, we can easily represent the original one as a concatenation like this:

$[a,k_1) + [k_1,k_2) + [k_2,k_3) + ... + [k_{N-1},b)$

The middle points (k_i) being excluded on one end, and included on the other end, allows easy concatenation and splitting.

Let us see an example with the `bytearray` type:

```
>>> bytearray()  # empty bytearray object
bytearray(b'')
>>> bytearray(10)  # zero-filled instance with given length
bytearray(b'\x00\x00\x00\x00\x00\x00\x00\x00\x00\x00')
>>> bytearray(range(5))  # bytearray from iterable of integers
bytearray(b'\x00\x01\x02\x03\x04')
>>> name = bytearray(b"Lina")  #A - bytearray from bytes
>>> name.replace(b"L", b"l")
bytearray(b'lina')
>>> name.endswith(b'na')
True
>>> name.upper()
bytearray(b'LINA')
>>> name.count(b'L')
1
```

As you can see, there are a few ways to create a `bytearray` object. They can be useful in many situations; for example, when receiving data through a socket, they eliminate the need to concatenate data while polling, hence they can prove to be very handy. On line `#A`, we created a `bytearray` named `name` from the bytes literal `b'Lina'` to show you how the `bytearray` object exposes methods from both sequences and strings, which is extremely handy. If you think about it, they can be considered mutable strings.

Set types

Python also provides two set types, `set` and `frozenset`. The `set` type is mutable, while `frozenset` is immutable. They are unordered collections of immutable objects. When printed, they are usually represented as comma-separated values, within a pair of curly braces.

Hashability is a characteristic that allows an object to be used as a set member as well as a key for a dictionary, as we will see very soon.

From the official documentation (`https://docs.python.org/3.12/glossary.html#term-hashable`):

> *"An object is* **hashable** *if it has a hash value which never changes during its lifetime, and can be compared to other objects. [...] Hashability makes an object usable as a dictionary key and a set member, because these data structures use the hash value internally. Most of Python's immutable built-in objects are hashable; mutable containers (such as lists or dictionaries) are not; immutable containers (such as tuples and frozensets) are only hashable if their elements are hashable. Objects which are instances of user-defined classes are hashable by default. They all compare unequal (except with themselves), and their hash value is derived from their* `id()`*."*

Objects that compare equal must have the same hash value. Sets are very commonly used to test for membership; let us introduce the `in` operator in the following example:

```
>>> small_primes = set()  # empty set
>>> small_primes.add(2)  # adding one element at a time
>>> small_primes.add(3)
>>> small_primes.add(5)
>>> small_primes
{2, 3, 5}
```

```
>>> small_primes.add(1)  # 1 is not a prime!
>>> small_primes
{1, 2, 3, 5}
>>> small_primes.remove(1)  # so let us remove it
>>> 3 in small_primes  # membership test
True
>>> 4 in small_primes
False
>>> 4 not in small_primes  # negated membership test
True
>>> small_primes.add(3)  # trying to add 3 again
>>> small_primes
{2, 3, 5}  # no change, duplication is not allowed
>>> bigger_primes = set([5, 7, 11, 13])  # faster creation
>>> small_primes | bigger_primes  # union operator `|`
{2, 3, 5, 7, 11, 13}
>>> small_primes & bigger_primes  # intersection operator `&`
{5}
>>> small_primes - bigger_primes  # difference operator `-`
{2, 3}
```

In the preceding code, you can see two ways to create a set. One creates an empty set and then adds elements one at a time. The other creates the set using a list of numbers as an argument to the constructor, which does all the work for us. Of course, you can create a set from a list or tuple (or any iterable) and then you can add and remove members from the set as you please.

We will look at **iterable** objects and iteration in the next chapter. For now, just know that iterable objects are objects you can iterate on in a direction.

Another way of creating a set is by simply using the curly braces notation, like this:

```
>>> small_primes = {2, 3, 5, 5, 3}
>>> small_primes
{2, 3, 5}
```

Notice we added some duplication to emphasize that the resulting set will not have any. Let us see an example using the immutable counterpart of the set type, `frozenset`:

```
>>> small_primes = frozenset([2, 3, 5, 7])
>>> bigger_primes = frozenset([5, 7, 11])
>>> small_primes.add(11)  # we cannot add to a frozenset
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
AttributeError: 'frozenset' object has no attribute 'add'
>>> small_primes.remove(2)  # neither we can remove
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
AttributeError: 'frozenset' object has no attribute 'remove'
>>> small_primes & bigger_primes  # intersect, union, etc. allowed
frozenset({5, 7})
```

As you can see, `frozenset` objects are quite limited with respect to their mutable counterpart. They still prove very effective for membership tests, union, intersection, and difference operations, and for performance reasons.

Mapping types: dictionaries

Of all the built-in Python data types, the dictionary is easily the most interesting. It is the only standard mapping type, and it is the backbone of every Python object.

A dictionary maps keys to values. Keys need to be hashable objects, while values can be of any arbitrary type. Dictionaries are also mutable objects. There are quite a few ways to create a dictionary, so let us give you a simple example of five ways to create a dictionary:

```
>>> a = dict(A=1, Z=-1)
>>> b = {"A": 1, "Z": -1}
>>> c = dict(zip(["A", "Z"], [1, -1]))
>>> d = dict([("A", 1), ("Z", -1)])
>>> e = dict({"Z": -1, "A": 1})
>>> a == b == c == d == e  # are they all the same?
True  # They are indeed
```

All these dictionaries map the key `A` to the value `1`, and `Z` to the value `-1`.

Did you notice those double equals? Assignment is done with one equal, while to check whether an object is the same as another one (or five in one go, in this case), we use double equals. There is also another way to compare objects, which involves the `is` operator, and checks whether the two objects are the same (that is, that they have the same ID, not just the same value), but unless you have a good reason to use it, you should use the double equals instead.

In the preceding code, we also used one nice function: `zip()`. It is named after the real-life zip, which glues together two parts, taking one element from each part at a time. Let us show you an example:

```
>>> list(zip(["h", "e", "l", "l", "o"], [1, 2, 3, 4, 5]))
[('h', 1), ('e', 2), ('l', 3), ('l', 4), ('o', 5)]
>>> list(zip("hello", range(1, 6)))  # equivalent, more pythonic
[('h', 1), ('e', 2), ('l', 3), ('l', 4), ('o', 5)]
```

In the preceding example, we have created the same list in two different ways, one more explicit, and the other a little bit more Pythonic. Forget for a moment that we had to wrap the `list()` constructor around the `zip()` call (the reason is `zip()` returns an iterator, not a `list`, so if we want to see the result, we need to exhaust that iterator into something—a list in this case), and concentrate on the result. See how `zip()` has coupled the first elements of its two arguments together, then the second ones, then the third ones, and so on?

Take a look at the zip of a suitcase, a purse, or the cover of a pillow, and you will see it works exactly like the one in Python. But let us go back to dictionaries and see how many useful methods they expose for allowing us to manipulate them as we want. Let us start with the basic operations:

```
>>> d = {}
>>> d["a"] = 1  # let us set a couple of (key, value) pairs
>>> d["b"] = 2
>>> len(d)  # how many pairs?
2
>>> d["a"]  # what is the value of "a"?
1
>>> d  # how does `d` look now?
{'a': 1, 'b': 2}
>>> del d["a"]  # let us remove `a`
>>> d
{'b': 2}
>>> d["c"] = 3  # let us add "c": 3
>>> "c" in d  # membership is checked against the keys
True
>>> 3 in d  # not the values
False
>>> "e" in d
False
```

```
>>> d.clear()  # let us clean everything from this dictionary
>>> d
{}
```

Notice how accessing keys of a dictionary, regardless of the type of operation we are performing, is done using square brackets. Do you remember strings, lists, and tuples? We were accessing elements at some position through square brackets as well, which is yet another example of Python's consistency.

Let us now look at three special objects called **dictionary views**: `keys`, `values`, and `items`. These objects provide a dynamic view of the dictionary entries. They change when the dictionary changes. `keys()` returns all the keys in the dictionary, `values()` returns all the values in the dictionary, and `items()` returns all the *(key, value)* pairs in the dictionary, as a list of 2-tuples.

Let us exercise all this with some code:

```
>>> d = dict(zip("hello", range(5)))
>>> d
{'h': 0, 'e': 1, 'l': 3, 'o': 4}
>>> d.keys()
dict_keys(['h', 'e', 'l', 'o'])
>>> d.values()
dict_values([0, 1, 3, 4])
>>> d.items()
dict_items([('h', 0), ('e', 1), ('l', 3), ('o', 4)])
>>> 3 in d.values()
True
>>> ("o", 4) in d.items()
True
```

There are a few things to note here. First, notice how we are creating a dictionary by iterating over the zipped version of the string `'hello'` and the numbers `0, 1, 2, 3, 4`. The string `'hello'` has two `'l'` characters inside, and they are paired up with the values 2 and 3 by the `zip()` function. Notice how in the dictionary, the second occurrence of the `'l'` key (the one with the value 3), overwrites the first one (the one with the value 2). This is because every key in a dictionary must be unique. Another thing to notice is that when asking for any view, the original order in which items were added is preserved.

We will see how these views are fundamental tools when we discuss iterating over collections. For now, let us look at some other useful methods exposed by Python's dictionaries:

```
>>> d
{'h': 0, 'e': 1, 'l': 3, 'o': 4}
>>> d.popitem()  # removes the last item added
('o', 4)
>>> d
{'h': 0, 'e': 1, 'l': 3}
>>> d.pop("l")  # remove item with key `l`
3
>>> d.pop("not-a-key")  # remove a key not in dictionary: KeyError
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
KeyError: 'not-a-key'
>>> d.pop("not-a-key", "default-value")  # with a default value?
'default-value'  # we get the default value
>>> d.update({"another": "value"})  # we can update dict this way
>>> d.update(a=13)  # or this way (like a function call)
>>> d
{'h': 0, 'e': 1, 'another': 'value', 'a': 13}
>>> d.get("a")  # same as d['a'] but if key is missing no KeyError
13
>>> d.get("a", 177)  # default value used if key is missing
13
>>> d.get("b", 177)  # like in this case
177
>>> d.get("b")  # key is not there, so None is returned
```

All these methods are quite simple to understand, but it is worth talking about that `None` for a moment. Every function in Python returns `None` unless the `return` statement is explicitly used to return something else. We will see this in depth when we explore functions in *Chapter 4*, *Functions, the Building Blocks of Code*. `None` is frequently used to represent the absence of a value, and it is quite commonly used as a default value for arguments in function declarations. Inexperienced coders may sometimes write functions that return either `False` or `None`. Both `False` and `None` evaluate to `False` in a Boolean context, so it may seem that there is not much difference between them. But actually, we would argue that there is an important difference: `False` means that we have information, and the information we have is `False`.

`None` means *no information*; no information is very different from information that is `False`. In plain language, if you ask your mechanic *Is my car ready?*, there is a big difference between the answer *No, it is not* (`False`) and *I have no idea* (`None`).

One last method we really like about dictionaries is `setdefault()`. The `setdefault()` method behaves like the `get()` one. When called, it will also set the `key/value` pair into the dictionary. Let us see an example:

```
>>> d = {}
>>> d.setdefault("a", 1)  # "a" is missing, we get default value
1
>>> d
{'a': 1}  # also, the key/value pair ("a", 1) has now been added
>>> d.setdefault("a", 5)  # let us try to override the value
1
>>> d
{'a': 1}  # no override, as expected
```

This brings us to the end of this tour of dictionaries. Test your knowledge about them by trying to predict what `d` looks like after this line:

```
>>> d = {}
>>> d.setdefault("a", {}).setdefault("b", []).append(1)
```

Do not worry if it is not immediately obvious to you. We just want to encourage you to experiment with dictionaries.

Python 3.9 added a new union operator, available for `dict` objects, which was introduced by **PEP 584**. When it comes to applying union to `dict` objects, we need to remember that union for them is not commutative. This becomes evident when the two `dict` objects we are merging have one or more keys in common. Check out this example:

```
>>> d = {"a": "A", "b": "B"}
>>> e = {"b": 8, "c": "C"}
>>> d | e
{'a': 'A', 'b': 8, 'c': 'C'}
>>> e | d
{'b': 'B', 'c': 'C', 'a': 'A'}
>>> {**d, **e}
{'a': 'A', 'b': 8, 'c': 'C'}
>>> {**e, **d}
```

```
{'b': 'B', 'c': 'C', 'a': 'A'}
>>> d |= e
>>> d
{'a': 'A', 'b': 8, 'c': 'C'}
```

Here, the `dict` objects `d` and `e` have the key `'b'` in common. In `d`, the value associated with `'b'` is `'B'`; whereas, in `e`, it is the number 8. This means that when we merge the two, with `e` on the righthand side of the union operator, `|`, the value in `e` overrides the one in `d`. The opposite happens, of course, when we swap the positions of those objects in relation to the union operator.

In this example, you can also see how the union can be performed by using the ** operator to produce a **dictionary unpacking**. It is worth noting that union can also be performed as an augmented assignment operation (`d |= e`), which works in place. Please refer to PEP 584 for more information about this feature.

This completes our tour of built-in data types. Before we conclude this chapter, we want to take a brief look at other data types provided by the standard library.

Data types

Python provides a variety of specialized data types, such as dates and times, container types, and enumerations. There is a whole section in the Python standard library titled *Data Types*, which deserves to be explored; it is filled with interesting and useful tools for every programmer's needs. You can find it here: `https://docs.python.org/3/library/datatypes.html`.

In this section, we will give you a brief introduction to dates and times, collections, and enumerations.

Dates and times

The Python standard library provides several data types that can be used to deal with dates and times. This may seem like a simple topic at first, but time zones, daylight saving time, leap years, and other quirks can easily trip up an unwary programmer. There are also a huge number of ways to format and localize date and time information. This, in turn, makes it challenging to parse dates and times. This is probably why it is quite common for professional Python programmers to also rely on various third-party libraries to provide some much-needed extra power when working with dates and times.

The standard library

We will start with the standard library and finish the session with a little overview of what is out there in terms of the third-party libraries you can use.

From the standard library, the main modules that are used to handle dates and times are `datetime`, `calendar`, `zoneinfo`, and `time`. Let us start with the imports you will need for this whole section:

```
>>> from datetime import date, datetime, timedelta, timezone, UTC
>>> import time
>>> import calendar as cal
>>> from zoneinfo import ZoneInfo
```

The first example deals with dates. Let us see how they look:

```
>>> today = date.today()
>>> today
datetime.date(2024, 3, 19)
>>> today.ctime()
'Tue Mar 19 00:00:00 2024'
>>> today.isoformat()
'2024-03-19'
>>> today.weekday()
1
>>> cal.day_name[today.weekday()]
'Tuesday'
>>> today.day, today.month, today.year
(19, 3, 2024)
>>> today.timetuple()
time.struct_time(
    tm_year=2024, tm_mon=3, tm_mday=19,
    tm_hour=0, tm_min=0, tm_sec=0,
    tm_wday=1, tm_yday=79, tm_isdst=-1
)
```

We start by fetching the date for today. We can see that it is an instance of the `datetime.date` class. Then we get two different representations for it, following the **C** and the **ISO 8601** format standards, respectively. After that, we ask what day of the week it is, and we get the number 1. Days are numbered 0 to 6 (representing Monday to Sunday), so we grab the value of the sixth element in `calendar.day_name` (notice in the code that we have aliased `calendar` with `cal` for brevity).

The last two instructions show how to get detailed information out of a date object. We can inspect its `day`, `month`, and `year` attributes, or call the `timetuple()` method and get a whole wealth of information. Since we are dealing with a date object, notice that all the information about time has been set to `0`.

Let us now play with time:

```
>>> time.ctime()
'Tue Mar 19 21:15:23 2024'
>>> time.daylight
1
>>> time.gmtime()
time.struct_time(
    tm_year=2024, tm_mon=3, tm_mday=19,
    tm_hour=21, tm_min=15, tm_sec=53,
    tm_wday=1, tm_yday=79, tm_isdst=0
)
>>> time.gmtime(0)
time.struct_time(
    tm_year=1970, tm_mon=1, tm_mday=1,
    tm_hour=0, tm_min=0, tm_sec=0,
    tm_wday=3, tm_yday=1, tm_isdst=0
)
>>> time.localtime()
time.struct_time(
    tm_year=2024, tm_mon=3, tm_mday=19,
    tm_hour=21, tm_min=16, tm_sec=6,
    tm_wday=1, tm_yday=79, tm_isdst=0
)
>>> time.time()
1710882970.789991
```

This example is quite similar to the one before, only here, we are dealing with time. We can see how to get a printed representation of time according to the C format standard, and then how to check if daylight saving time is in effect. The `gmtime` function converts a given number of seconds from the epoch to a `struct_time` object in UTC. If we don't feed it a number, it will use the current time.

The **epoch** is a date and time from which a computer system measures system time. You can see that, on the machine used to run this code, the epoch is January 1st, 1970. This is the point in time used by both Unix and POSIX. Coordinated Universal Time or **UTC** is the primary time standard by which the world regulates clocks and time.

We finish the example by getting the `struct_time` object for the current local time and the number of seconds from the epoch expressed as a float number (`time.time()`).

Let us now see an example using `datetime` objects, which combine dates and times.

```
>>> now = datetime.now()
>>> utcnow = datetime.now(UTC)
>>> now
datetime.datetime(2024, 3, 19, 21, 16, 56, 931429)
>>> utcnow
datetime.datetime(
    2024, 3, 19, 21, 17, 53, 241072,
    tzinfo=datetime.timezone.utc
)
>>> now.date()
datetime.date(2024, 3, 19)
>>> now.day, now.month, now.year
(19, 3, 2024)
>>> now.date() == date.today()
True
>>> now.time()
datetime.time(21, 16, 56, 931429)
>>> now.hour, now.minute, now.second, now.microsecond
(21, 16, 56, 931429)
>>> now.ctime()
'Tue Mar 19 21:16:56 2024'
>>> now.isoformat()
'2024-03-19T21:16:56.931429'
>>> now.timetuple()
time.struct_time(
```

```
    tm_year=2024, tm_mon=3, tm_mday=19,
    tm_hour=21, tm_min=16, tm_sec=56,
    tm_wday=1, tm_yday=79, tm_isdst=-1
)
>>> now.tzinfo
>>> utcnow.tzinfo
datetime.timezone.utc
>>> now.weekday()
1
```

The preceding example is rather self-explanatory. We start by setting up two instances that represent the current time. One is related to UTC (`utcnow`), and the other one is a local representation (`now`).

You can get `date`, `time`, and specific attributes from a `datetime` object in a similar way to what we have already seen. It is also worth noting that `now` and `utcnow` have different values for the `tzinfo` attribute. `now` is a **naïve** object, while `utcnow` is not.

Date and time objects may be categorized as *aware* if they include time zone information, or *naïve* if they don't.

Let us now see how a duration is represented in this context:

```
>>> f_bday = datetime(
    1975, 12, 29, 12, 50, tzinfo=ZoneInfo('Europe/Rome')
)
>>> h_bday = datetime(
    1981, 10, 7, 15, 30, 50, tzinfo=timezone(timedelta(hours=2))
)
>>> diff = h_bday - f_bday
>>> type(diff)
<class 'datetime.timedelta'>
>>> diff.days
2109
>>> diff.total_seconds()
182223650.0
>>> today + timedelta(days=49)
datetime.date(2024, 5, 7)
```

```
>>> now + timedelta(weeks=7)
datetime.datetime(2024, 5, 7, 21, 16, 56, 931429)
```

Two objects have been created that represent Fabrizio and Heinrich's birthdays. This time, in order to show you an alternative, we have created **aware** objects.

There are several ways to include time zone information when creating a `datetime` object, and in this example, we are showing you two of them. One uses the `ZoneInfo` object from the `zoneinfo` module, introduced in Python 3.9. The second one uses a simple `timedelta`, an object that represents a duration.

We then create the `diff` object, which is assigned as the subtraction of them. The result of that operation is an instance of `timedelta`. You can see how we can interrogate the `diff` object to tell us how many days Fabrizio and Heinrich's birthdays are apart, and even the number of seconds that represent that whole duration. Notice that we need to use `total_seconds()`, which expresses the whole duration in seconds. The `seconds` attribute represents the number of seconds assigned to that duration. So, a `timedelta(days=1)` will have seconds equal to 0 and `total_seconds()` equal to 86,400 (which is the number of seconds in a day).

Combining a `datetime` with a duration adds or subtracts that duration from the original date and time information. In the last few lines of the example, we can see how adding a duration to a `date` object produces a `date` as a result, whereas adding it to a `datetime` produces a `datetime`, as it is fair to expect.

One of the more difficult undertakings to carry out using dates and times is parsing. Let us see a short example:

```
>>> datetime.fromisoformat('1977-11-24T19:30:13+01:00')
datetime.datetime(
    1977, 11, 24, 19, 30, 13,
    tzinfo=datetime.timezone(datetime.timedelta(seconds=3600))
)
>>> datetime.fromtimestamp(time.time())
datetime.datetime(2024, 3, 19, 21, 26, 56, 785166)
```

We can easily create `datetime` objects from ISO-formatted strings, as well as from timestamps. However, in general, parsing a date from unknown formats can prove to be a difficult task.

Third-party libraries

To finish off this subsection, we would like to mention a few third-party libraries that you will very likely come across when dealing with dates and times in your code:

- **dateutil**: Powerful extensions to `datetime` (`https://dateutil.readthedocs.io/`)
- **Arrow**: Better dates and times for Python (`https://arrow.readthedocs.io/`)
- **Pendulum**: Python datetimes made easy (`https://pendulum.eustace.io/`)
- **Maya**: Datetimes for humans™ (`https://github.com/kennethreitz/maya`)
- **Delorean**: Time Travel Made Easy (`https://delorean.readthedocs.io/`)
- **pytz**: World time zone definitions for Python (`https://pythonhosted.org/pytz/`)

These are some of the most common, and they are worth exploring.

Let us take a look at one final example, this time using the Arrow third-party library:

```
>>> import arrow
>>> arrow.utcnow()
<Arrow [2024-03-19T21:29:15.076737+00:00]>
>>> arrow.now()
<Arrow [2024-03-19T21:29:26.354786+00:00]>

>>> local = arrow.now("Europe/Rome")
>>> local
<Arrow [2024-03-19T22:29:40.282730+01:00]>
>>> local.to("utc")
<Arrow [2024-03-19T21:29:40.282730+00:00]>
>>> local.to("Europe/Moscow")
<Arrow [2024-03-20T00:29:40.282730+03:00]>
>>> local.to("Asia/Tokyo")
<Arrow [2024-03-20T06:29:40.282730+09:00]>
>>> local.datetime
datetime.datetime(
    2024, 3, 19, 22, 29, 40, 282730,
    tzinfo=tzfile('/usr/share/zoneinfo/Europe/Rome')
)
>>> local.isoformat()
'2024-03-19T22:29:40.282730+01:00'
```

Arrow provides a wrapper around the data structures of the standard library, plus a whole set of methods and helpers that simplify the task of dealing with dates and times. You can see from this example how easy it is to get the local date and time in the Italian time zone (*Europe/Rome*), as well as to convert it to UTC, or to the Russian or Japanese time zones. The last two instructions show how you can get the underlying `datetime` object from an Arrow one, and the very useful ISO-formatted representation of a date and time.

The collections module

When Python general-purpose built-in containers (`tuple`, `list`, `set`, and `dict`) aren't enough, we can find specialized container data types in the `collections` module. They are described in *Table 2.1*.

Data type	Description
`namedtuple()`	Factory function for creating tuple subclasses with named fields
`deque`	List-like container with fast appends and pops on either end
`ChainMap`	Dictionary-like class for creating a single view of multiple mappings
`Counter`	Dictionary subclass for counting hashable objects
`OrderedDict`	Dictionary subclass with methods that allow for re-ordering entries
`defaultdict`	Dictionary subclass that calls a factory function to supply missing values
`UserDict`	Wrapper around dictionary objects for easier dictionary subclassing
`UserList`	Wrapper around list objects for easier list subclassing
`UserString`	Wrapper around string objects for easier string subclassing

Table 2.1: Collections module data types

There is not enough space here to cover them all, but you can find plenty of examples in the official documentation; here, we will just give a small example to show you `namedtuple`, `defaultdict`, and `ChainMap`.

namedtuple

A **namedtuple** is a tuple-like object that has fields accessible by attribute lookup, as well as being indexable and iterable (it is actually a subclass of `tuple`). This is a compromise between a fully-fledged object and a tuple, and it can be useful in those cases where you do not need the full power of a custom object but only want your code to be more readable by avoiding positional indexing.

Another use case is when there is a chance that items in the tuple will need to change their position after refactoring, forcing the programmer to also refactor all the logic involved, which can be tricky.

For example, say we are handling data about the left and right eyes of a patient. We save one value for the left eye (position 0) and one for the right eye (position 1) in a regular tuple. Here is how that may look:

```
>>> vision = (9.5, 8.8)
>>> vision
(9.5, 8.8)
>>> vision[0]  # left eye (implicit positional reference)
9.5
>>> vision[1]  # right eye (implicit positional reference)
8.8
```

Now let us pretend we handle `vision` objects all of the time, and, at some point, the designer decides to enhance them by adding information for the combined vision, so that a `vision` object stores data in this format *(left eye, combined, right eye)*.

Do you see the trouble we're in now? We may have a lot of code that depends on `vision[0]` being the left eye information (which it still is) and `vision[1]` being the right eye information (which is no longer the case). We have to refactor our code wherever we handle these objects, changing `vision[1]` to `vision[2]`, and that can be painful. We could have probably approached this a bit better from the beginning, by using a `namedtuple`. Let us show you what we mean:

```
>>> from collections import namedtuple
>>> Vision = namedtuple('Vision', ['left', 'right'])
>>> vision = Vision(9.5, 8.8)
>>> vision[0]
9.5
>>> vision.left  # same as vision[0], but explicit
9.5
>>> vision.right  # same as vision[1], but explicit
8.8
```

If, within our code, we refer to the left and right eyes using `vision.left` and `vision.right`, all we need to do to fix the new design issue is change our factory and the way we create instances—the rest of the code won't need to change:

```
>>> Vision = namedtuple('Vision', ['left', 'combined', 'right'])
>>> vision = Vision(9.5, 9.2, 8.8)
>>> vision.left  # still correct
9.5
>>> vision.right  # still correct (though now is vision[2])
8.8
>>> vision.combined  # the new vision[1]
9.2
```

You can see how convenient it is to refer to those values by name rather than by position. After all, as a wise man once wrote, *Explicit is better than implicit*. This example may be a little extreme; of course, it is not likely that a decent programmer would choose to represent data in a simple tuple in the first place, but you'd be amazed to know how frequently issues similar to this one occur in a professional environment, and how complicated it is to refactor in such cases.

defaultdict

The **defaultdict** data type is one of our favorites. It allows you to avoid checking whether a key is in a dictionary by simply inserting it for you on your first access attempt, with a default value whose type you pass on creation. In some cases, this tool can be very handy and shorten your code a little. Let us see a quick example. Say we are updating the value of age by adding one year to it. If age is not there, we assume it was `0` and we update it to `1`:

```
>>> d = {}
>>> d["age"] = d.get("age", 0) + 1  # age not there, we get 0 + 1
>>> d
{'age': 1}
>>> d = {"age": 39}
>>> d["age"] = d.get("age", 0) + 1  # age is there, we get 40
>>> d
{'age': 40}
```

Now let us see how we could further simplify the first part of the code above, using a `defaultdict` data type:

```
>>> from collections import defaultdict
>>> dd = defaultdict(int)  # int is the default type (0 the value)
>>> dd["age"] += 1  # short for dd['age'] = dd['age'] + 1
>>> dd
defaultdict(<class 'int'>, {'age': 1})  # 1, as expected
```

Notice how we just need to instruct the `defaultdict` factory that we want an `int` number to be used if the key is missing (we will get 0, which is the default for the `int` type). Also notice that even though in this example there is no gain in the number of lines, there is definitely a gain in readability, which is very important. You can also use your own functions to customize what value will be assigned to missing keys. To learn more, please refer to the official documentation.

ChainMap

ChainMap is a useful data type which was introduced in Python 3.3. It behaves like a normal dictionary but, according to the Python documentation, *is provided for quickly linking a number of mappings so they can be treated as a single unit*. This is usually much faster than creating one dictionary and running multiple `update` calls on it. `ChainMap` can be used to simulate nested scopes and is useful in templating. The underlying mappings are stored in a list. That list is public and can be accessed or updated using the `maps` attribute. Lookups search the underlying mappings successively until a key is found. By contrast, writes, updates, and deletions only operate on the first mapping.

A very common use case is providing defaults, so let us see an example:

```
>>> from collections import ChainMap
>>> default_connection = {'host': 'localhost', 'port': 4567}
>>> connection = {'port': 5678}
>>> conn = ChainMap(connection, default_connection) # map creation
>>> conn['port']  # port is found in the first dictionary
5678
>>> conn['host']  # host is fetched from the second dictionary
'localhost'
>>> conn.maps  # we can see the mapping objects
[{'port': 5678}, {'host': 'localhost', 'port': 4567}]
>>> conn['host'] = 'packtpub.com'  # let's add host
>>> conn.maps
[{'port': 5678, 'host': 'packtpub.com'},
 {'host': 'localhost', 'port': 4567}]
>>> del conn['port']  # let's remove the port information
>>> conn.maps
[{'host': 'packtpub.com'}, {'host': 'localhost', 'port': 4567}]
>>> conn['port']  # now port is fetched from the second dictionary
4567
```

```
>>> dict(conn)  # easy to merge and convert to regular dictionary
{'host': 'packtpub.com', 'port': 4567}
```

This is yet another example of how Python simplifies things for us. You work on a `ChainMap` object, configure the first mapping as you want, and when you need a complete dictionary with all the defaults as well as the customized items, you can just feed the `ChainMap` object to a `dict` constructor. If you have ever coded in other languages, such as Java or C++, you probably will be able to appreciate how precious this is, and how well Python simplifies some tasks.

Enums

Living in the `enum` module, and definitely worth mentioning, are **enumerations**. They were introduced in Python 3.4, and we thought it would be a good idea to give you an example on them for the sake of completeness.

The official definition of an enumeration is that it is *a set of symbolic names (members) bound to unique, constant values. Within an enumeration, the members can be compared by identity, and the enumeration itself can be iterated over*.

Say you need to represent traffic lights; in your code, you might resort to the following:

```
>>> GREEN = 1
>>> YELLOW = 2
>>> RED = 4
>>> TRAFFIC_LIGHTS = (GREEN, YELLOW, RED)
>>> # or with a dict
>>> traffic_lights = {"GREEN": 1, "YELLOW": 2, "RED": 4}
```

There's nothing special about this code. It is something, in fact, that is very common to find. But, consider doing this instead:

```
>>> from enum import Enum
>>> class TrafficLight(Enum):
...     GREEN = 1
...     YELLOW = 2
...     RED = 4
...
>>> TrafficLight.GREEN
<TrafficLight.GREEN: 1>
>>> TrafficLight.GREEN.name
'GREEN'
```

```
>>> TrafficLight.GREEN.value
1
>>> TrafficLight(1)
<TrafficLight.GREEN: 1>
>>> TrafficLight(4)
<TrafficLight.RED: 4>
```

Ignoring for a moment the (relative) complexity of a class definition, you can appreciate how advantageous this approach may be. The data structure is much cleaner, and the API it provides is much more powerful. We encourage you to check out the official documentation to explore all the features you can find in the `enum` module. We think it is worth exploring, at least once.

Final considerations

That is it. Now you have seen a very good proportion of the data structures that you will use in Python. We encourage you to experiment further with every data type we have seen in this chapter. We also suggest that you skim through the official documentation, just to get an idea of what is available to you when writing Python. That working knowledge can be quite useful when you find it difficult to properly represent data using the most common types.

Before we leap into *Chapter 3*, *Conditionals and Iteration*, we would like to share some final considerations about some aspects that, to our minds, are important and not to be neglected.

Small value caching

While discussing objects at the beginning of this chapter, we saw that when we assign a name to an object, Python creates the object, sets its value, and then points the name to it. We can assign different names to the same value, and we expect different objects to be created, like this:

```
>>> a = 1000000
>>> b = 1000000
>>> id(a) == id(b)
False
```

In the preceding example, `a` and `b` are assigned to two `int` objects, which have the same value, but they are not the same object—as you can see, their `id` is not the same. Let us try with a smaller value:

```
>>> a = 5
>>> b = 5
>>> id(a) == id(b)
True
```

Uh-oh! This, we didn't expect! Why are the two objects the same now? We didn't do `a = b = 5`; we set them up separately. The answer is something called object interning.

Object interning is a memory optimization technique that is used primarily for immutable data types, such as strings and integers in Python. The idea is to reuse existing objects instead of creating new ones every time an object with the same value is required.

This can lead to significant memory savings and performance improvements because it reduces the load on the garbage collector and speeds up comparisons since they can be done by comparing object identities.

Everything is handled properly, under the hood, so you do not need to worry, but it's important to know about this feature for those cases where we deal directly with IDs.

How to choose data structures

As we've seen, Python provides you with several built-in data types and, sometimes, if you're not that experienced, choosing the one that serves you best can be tricky, especially when it comes to collections. For example, say you have many dictionaries to store, each of which represents a customer. Within each customer dictionary, there's a unique identification code with the key `"id"`. In what kind of collection would you place them? Well, unless we know more about these customers, it might be hard to produce an answer. We need to ask questions. What kind of access do we need? What sort of operations do we need to perform on each item? How many times? Will the collection change over time? Will we need to modify the customer dictionaries in any way? What is going to be the most frequent operation we have to perform on the collection?

If you can answer those questions, then you will know what to choose. If the collection never shrinks or grows (in other words, it won't need to add/delete any customer object after creation) or shuffles, then tuples are a possible choice. Otherwise, lists are a good candidate. Every customer dictionary has a unique identifier though, so even a dictionary could work. Let us draft these options for you:

```
customer1 = {"id": "abc123", "full_name": "Master Yoda"}
customer2 = {"id": "def456", "full_name": "Obi-Wan Kenobi"}
customer3 = {"id": "ghi789", "full_name": "Anakin Skywalker"}
# collect them in a tuple
customers = (customer1, customer2, customer3)
# or collect them in a list
customers = [customer1, customer2, customer3]
# or maybe within a dictionary, they have a unique id after all
```

```
customers = {
    "abc123": customer1,
    "def456": customer2,
    "ghi789": customer3,
}
```

Some customers we have there, right? We probably would not go with the tuple option, unless we wanted to highlight that the collection is not going to change or to suggest it shouldn't be modified. We would say that, usually, a list is better, as it allows for more flexibility.

Another factor to keep in mind is that tuples and lists are ordered collections. If you use a set, for example, you would lose the ordering, so you need to know if ordering is important in your application.

What about performance? For example, in a list, operations such as insertion and membership testing can take *O(n)* time, while they are *O(1)* for a dictionary. It is not always possible to use dictionaries though, if we don't have the guarantee that we can uniquely identify each item of the collection by means of one of its properties and that the property in question is hashable (so it can be a key in `dict`).

If you're wondering what *O(n)* and *O(1)* mean, please research **big O notation**. In this context, let us just say that if performing an operation *Op* on a data structure takes *O(f(n))*, it would mean that *Op* takes at most time $t \leq c * f(n)$ to complete, where c is some positive constant, n is the size of the input, and f is some function. So, think of *O(...)* as an upper bound for the running time of an operation (it can also be used to size other measurable quantities, of course).

Another way of understanding whether you have chosen the right data structure is by looking at the code you have to write in order to manipulate it. If writing the logic comes easily and flows naturally, then you probably have chosen correctly, but if you find yourself thinking your code is getting unnecessarily complicated, then you may need to reconsider your choices. It is quite hard to give advice without a practical case though, so when you choose a data structure for your data, try to keep ease of use and performance in mind, and give precedence to what matters most in the context you are in.

About indexing and slicing

At the beginning of this chapter, we saw slicing applied to strings. Slicing, in general, applies to a sequence: tuples, lists, strings, and so on. With lists, slicing can also be used for assignment, although in practice this technique is rarely used—at least in our experience. Dictionaries and sets cannot be sliced, of course. Let us discuss indexing a bit more in depth.

There is one characteristic regarding Python indexing that we haven't mentioned before. We will show you by way of an example. How do you address the last element of a collection? Let us see:

```
>>> a = list(range(10))  # `a` has 10 elements. Last one is 9.
>>> a
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
>>> len(a)  # its length is 10 elements
10
>>> a[len(a) - 1]  # position of last one is len(a) - 1
9
>>> a[-1]  # but we don't need len(a)! Python rocks!
9
>>> a[-2]  # equivalent to len(a) - 2
8
>>> a[-3]  # equivalent to len(a) - 3
7
```

If list `a` has 10 elements, then due to the 0-index positioning system of Python, the first one is at position 0 and the last one is at position 9. In the preceding example, the elements are conveniently placed in a position equal to their value: `0` is at position 0, `1` at position 1, and so on.

So, in order to fetch the last element, we need to know the length of the whole list (or tuple, string, and so on) and then subtract 1, hence `len(a) - 1`. This is so common an operation that Python provides you with a way to retrieve elements using **negative indexing**. This proves quite useful as it simplifies the code. *Figure 2.2* displays a neat diagram about how indexing works on the string `"HelloThere"` (which is Obi-Wan Kenobi sarcastically greeting General Grievous in *Star Wars: Episode III—Revenge of the Sith*):

Figure 2.2: Python indexing

Trying to address indexes greater than 9 or smaller than -10 will raise an `IndexError`, as expected.

About names

You may have noticed that, in order to keep the examples as short as possible, we have named many objects using simple letters, like `a`, `b`, `c`, `d`, and so on. This is perfectly fine when debugging on the console, or showing that `a + b == 7`, but it is bad practice when it comes to professional code (or any type of code, for that matter). We hope you will indulge us where we have done it; the reason is to present the code in a more compact way.

In a real environment though, when you choose names for your data, you should choose them carefully—they should reflect what the data is about. So, if you have a collection of `Customer` objects, `customers` is a perfectly good name for it. Would `customers_list`, `customers_tuple`, or `customers_collection` work as well? Think about it for a second. Is it good to tie the name of the collection to the datatype? We do not think so unless there is a compelling reason. The reasoning behind this is that once `customers_tuple` starts being used in different parts of your code, and you realize you actually want to use a list instead of a tuple, you have a name tied to the wrong data type, which means you will have to refactor. Names for data should be nouns, and names for functions should be verbs. Names should be as expressive as possible. Python is actually a very good example when it comes to names. Most of the time, you can just guess what a function is called if you know what it does.

Chapter 2 of the book *Clean Code* by *Robert C. Martin* is entirely dedicated to names. It is a great book that helped us improve our coding style in many different ways—a must-read, if you want to take your skills to the next level.

Summary

In this chapter, we explored Python's built-in data types. We have seen how many there are and how much can be achieved just by using them in different combinations.

We have seen number types, sequences, sets, mappings, dates, times, collections, and enumerations. We have also seen that everything is an object and learned the difference between mutable and immutable. We also learned about slicing and indexing.

We presented the cases with simple examples, but there is much more that you can learn about this subject, so stick your nose into the official documentation and go exploring!

Most of all, we encourage you to try out all the exercises by yourself—get your fingers used to that code, build some muscle memory, and experiment, experiment, experiment. Learn what happens when you divide by zero, when you combine different number types, and when you work with strings. Play with all data types. Exercise them, break them, discover all their methods, enjoy them, and learn them very, very well. If your foundation is not rock solid, how good can your code be? Data is the foundation for everything; data shapes what dances around it.

The more you progress with the book, the more likely it is that you will find some discrepancies or a small typo here and there in our code (or yours). You will get an error message or something will break. That is wonderful! When you code, things break and you have to debug them, all the time, so consider errors as useful exercises to learn something new about the language you're using, and not as failures or problems. Errors will keep coming up, that is certain, so you may as well start making your peace with them now.

The next chapter is about conditionals and iteration. We will see how to actually put collections to use and make decisions based on the data that we are presented with. We will start to go a little faster now that your knowledge is building up, so make sure you are comfortable with the contents of this chapter before you move on to the next one. Once more, have fun, explore, and break things—it is a very good way to learn.

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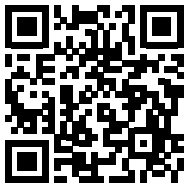

3

Conditionals and Iteration

> *"Would you tell me, please, which way I ought to go from here?"*
>
> *"That depends a good deal on where you want to get to."*
>
> *—Lewis Carroll, from Alice's Adventures in Wonderland*

In the previous chapter, we looked at Python's built-in data types. Now that you are familiar with data in its many forms and shapes, it is time to start looking at how a program can use it.

According to Wikipedia:

> *In computer science,* **control flow** *(or* **flow of control***) is the order in which individual statements, instructions, or function calls of an imperative program are executed or evaluated.*

The two main ways of controlling the flow of a program are **conditional programming** (also known as **branching**) and **looping**. These techniques can be combined to produce an endless variety of programs. Rather than attempting to document all the ways of combining looping and branching, we will give you an overview of the flow control constructs available in Python. Then, we will walk you through a couple of example programs. This way, you should get a better feeling of how conditional programming and looping can be used.

In this chapter, we are going to cover the following:

- Conditional programming
- Looping in Python
- Assignment expressions
- A quick peek at the `itertools` module

Conditional programming

Conditional programming, or branching, is something you do every moment of every day. Essentially, it consists of evaluating conditions and deciding what action to take: *if the light is green, then I can cross*; *if it is raining, then I am taking the umbrella*; and *if I am late for work, then I will call my manager*.

The if statement

The main tool for conditional programming in Python is the `if` statement. Its function is to evaluate an expression and, based on the result, choose which part of the code to execute. As usual, let us look at an example:

```
# conditional.1.py
late = True
if late:
    print("I need to call my manager!")
```

This is the simplest example possible: the `if` statement evaluates the expression `late` in a Boolean context (exactly as if we were calling `bool(late)`). If the result of the evaluation is `True`, then we enter the body of the code immediately after the `if` statement. Notice that the `print` instruction is indented, which means that it belongs to a scope defined by the `if` clause. Execution of this code yields:

```
$ python conditional.1.py
I need to call my manager!
```

Since `late` is `True`, the `print()` statement was executed. We can expand on the basic `if` statement, by adding an `else` clause. This provides an alternative set of instructions to execute when the expression in the `if` clause evaluates to `False`.

```
# conditional.2.py
late = False
if late:
```

```
    print("I need to call my manager!")  # 1
else:
    print("no need to call my manager...")  # 2
```

This time, we set `late = False`, so when we execute the code, the result is different:

```
$ python conditional.2.py
no need to call my manager...
```

Depending on the result of evaluating `late`, we can either enter block `# 1` or block `# 2`, *but not both*. Block `# 1` is executed when `late` evaluates to `True`, while block `# 2` is executed when `late` evaluates to `False`. Try assigning `False`/`True` values to `late` and see how the output changes.

A specialized else: elif

What we have seen so far is sufficient when you have only one condition to evaluate and, at most, two alternative paths to take (the `if` and `else` clauses). Sometimes, however, there are situations where you have to evaluate more than one condition to choose from among multiple paths. To demonstrate this, we will need an example with a few more options to choose from.

This time, we will create a simple tax calculator. Suppose that taxes are determined as follows: if your income is less than $10,000, you do not need to pay any taxes. If it is between $10,000 and $30,000, you must pay 20% in taxes. If it is between $30,000 and $100,000, you pay 35% in taxes, and if you are fortunate enough to earn over $100,000, you must pay 45% in taxes. Let us translate this into Python code:

```
# taxes.py
income = 15000
if income < 10000:
    tax_coefficient = 0.0  # 1
elif income < 30000:
    tax_coefficient = 0.2  # 2
elif income < 100000:
    tax_coefficient = 0.35  # 3
else:
    tax_coefficient = 0.45  # 4

print(f"You will pay: ${income * tax_coefficient} in taxes")
```

When we execute this code, we get the following output:

```
$ python taxes.py
You will pay: $3000.0 in taxes
```

Let us go through the example one line at a time. We start by setting up the income value. In the example, your income is $15,000. We enter the `if` statement. Notice that, this time, we also introduced the `elif` clause, which is a contraction of `else-if`. It differs from a plain `else` clause in that it also has its own condition. The `if` expression of `income < 10000` evaluates to `False`; therefore, block `# 1` is not executed.

The control passes to the next condition: `elif income < 30000`. This one evaluates to `True`; therefore, block `# 2` is executed, and because of this, Python then resumes execution after the whole `if/elif/elif/else` construct (which we can just call the `if` statement from now on). There is only one instruction after the `if` statement: the `print()` call, which produces output telling us that we will pay `$3000.0` in taxes this year (*15,000 * 20%*). Notice that the order is mandatory: `if` comes first, then (optionally) as many `elif` clauses as you may need, and then (optionally) a single `else` clause.

No matter how many lines of code you may have within each block, when one of the conditions evaluates to `True`, the associated block is executed, and then execution resumes after the whole clause. If none of the conditions evaluates to `True` (for example, `income = 200000`), then the body of the `else` clause would be executed (block `# 4`). This example expands our understanding of the behavior of the `else` clause. Its block of code is executed when none of the preceding `if/elif/.../elif` expressions have evaluated to `True`.

Try to modify the value of `income` until you can comfortably execute any of the blocks at will. Also, test the behavior at the **boundaries** where the values of the Boolean expressions in the `if` and `elif` clauses change. It is crucial to test boundaries thoroughly to ensure the correctness of your code. Should we allow you to drive at 18 or 17? Are we checking your age with `age < 18` or `age <= 18`? You cannot imagine how many times we have had to fix subtle bugs that stemmed from using the wrong operator, so go ahead and experiment with the code. Change some instances of `<` to `<=`, and set `income` to be one of the boundary values (10,000, 30,000, or 100,000), as well as any value in between. See how the result changes, and get a good understanding of it before proceeding.

Nesting if statements

You can also nest `if` statements. Let us look at another example to show you how. Let us say, for example, that your program encounters an error. If the alert system is the console, we print the error.

If the alert system is an email, the severity of the error determines which address we should send the alert to. If the alert system is anything other than the console or email, we do not know what to do, so we do nothing. Let us put this into code:

```
# errorsalert.py
alert_system = "console"  # other value can be "email"
error_severity = "critical"  # other values: "medium" or "low"
error_message = "Something terrible happened!"

if alert_system == "console":  # outer
    print(error_message)  # 1
elif alert_system == "email":
    if error_severity == "critical":  # inner
        send_email("admin@example.com", error_message)  # 2
    elif error_severity == "medium":
        send_email("support.1@example.com", error_message)  # 3
    else:
        send_email("support.2@example.com", error_message)  # 4
```

Here, we have an *inner* `if` statement nested within the body of the `elif` clause of an *outer* `if` statement. Notice that the nesting is achieved by indenting the inner `if` statement.

Let us step through the code and see what happens. We start by assigning values to `alert_system`, `error_severity`, and `error_message`. When we enter the outer `if` statement, if `alert_system == "console"` evaluates to `True`, body `# 1` is executed, and nothing else happens. On the other hand, if `alert_system == "email"` evaluates to `True`, then we enter the inner `if` statement. In the inner `if` statement, the `error_severity` determines whether we send an email to an admin, first-level support, or second-level support (blocks `# 2`, `# 3`, and `# 4`). The `send_email()` function is not defined in this example, so trying to run it would give you an error. In the `errorsalert.py` module, which you can find in the source code of this book, we included a trick to redirect that call to a regular `print()` function, just so you can experiment on the console without actually sending an email. Try changing the values and see how it all works.

The ternary operator

The next thing we would like to show you is the **ternary operator.** In Python, this is also known as a **conditional expression.** It looks and behaves like a short, in-line version of an `if` statement. When you just want to choose between two values, depending on some condition, it is sometimes easier and more readable to use the ternary operator instead of a full `if` statement. For example, instead of:

```
# ternary.py
order_total = 247  # GBP

# classic if/else form
if order_total > 100:
    discount = 25  # GBP
else:
    discount = 0  # GBP
print(order_total, discount)
```

We could write:

```
# ternary.py
# ternary operator
discount = 25 if order_total > 100 else 0
print(order_total, discount)
```

For simple cases like this, we find it convenient to be able to express that logic in one line instead of four. Remember that, as a coder, you spend much more time reading code than writing it, so Python's conciseness is invaluable.

In some languages (like C or JavaScript), the ternary operator is even more concise. For example, the above could be written as:

```
discount = order_total > 100 ? 25 : 0;
```

Although Python's version is slightly more verbose, we think it more than makes up for that by being easier to read and understand.

Are you clear on how the ternary operator works? It is quite simple; `something if condition else something-else` evaluates to something `if` condition evaluates to `True`. Otherwise, if `condition` is `False`, the expression evaluates to `something-else`.

Pattern matching

Structural pattern matching, often just called **pattern matching**, is a relatively new feature that was introduced in Python 3.10 via PEP 634 (`https://peps.python.org/pep-0634`). It was partly inspired by the pattern matching capabilities of languages like Haskel, Erlang, Scala, Elixir, and Ruby.

Simply put, the `match` statement compares a value against one or more *patterns*, and then it executes the code block associated with the first pattern that matches. Let us see a simple example:

```
# match.py
day_number = 4
match day_number:
    case 1 | 2 | 3 | 4 | 5:
        print("Weekday")
    case 6:
        print("Saturday")
    case 7:
        print("Sunday")
    case _:
        print(f"{day_number} is not a valid day number")
```

We start by initializing `day_number` before entering the `match` statement. The `match` statement will attempt to match the value of `day_number` against a series of patterns, each of which is introduced by the **case** keyword. In our example, we have four patterns. The first `1 | 2 | 3 | 4 | 5` will match any of the values `1`, `2`, `3`, `4`, or `5`. This is known as an **OR pattern**; it consists of a number of sub-patterns separated by `|`. It matches when any of the sub-patterns (in this case, the literal values `1`, `2`, `3`, `4`, and `5`) match. The second and third patterns in our example just consist of the integer literals `6` and `7`, respectively. The final pattern, `_`, is a **wildcard pattern**; it is a catch-all that matches any value. A `match` statement can have at most one catch-all pattern, and if one is present, it must be the last pattern.

The body of the first case block whose pattern matches will be executed. Afterward, execution resumes below the `match` statement without evaluating any of the remaining patterns. If none of the patterns match, execution resumes below the `match` statement without executing any of the case bodies. In our example, the first pattern matches, so `print("Weekday")` is executed. Take some time to experiment with this example. Try changing the value of `day_number` and see what happens when you run it.

The `match` statement resembles the `switch/case` statements of languages like C++ and JavaScript. However, it is much more powerful than that. The variety of different kinds of patterns available and the ability to compose patterns allow you to do much more than a simple C++ `switch` statement. For example, Python allows you to match sequences, dictionaries, or even custom classes. You can also capture and assign values to names in patterns. We do not have space here to cover everything you can do with pattern matching, but we encourage you to study the tutorial in PEP 636 (`https://peps.python.org/pep-0636`) to learn more.

Now that you know everything about controlling the path of the code, let us move on to the next subject: *looping*.

Looping

If you have any experience with looping in other programming languages, you will find Python's way of looping a bit different. First of all, what is looping? **Looping** means being able to repeat the execution of a code block more than once, according to the loop parameters given. There are different looping constructs that serve different purposes, and Python has distilled all of them down to just two, which you can use to achieve everything you need. These are the `for` and `while` statements.

Although it is technically possible to use either of them for any task that requires looping, they do serve different purposes. We will explore this difference thoroughly in this chapter. By the end of it, you will know when to use a `for` loop and when to use a `while` loop.

The for loop

The `for` loop is used when looping over a sequence, such as a list, tuple, or collection of objects. Let us start with a simple example and expand on the concept to see what the Python syntax allows us to do:

```
# simple.for.py
for number in [0, 1, 2, 3, 4]:
    print(number)
```

This simple snippet of code, when executed, prints all numbers from `0` to `4`. The body of the `for` loop (the `print()` line) is executed once for each value in the list `[0, 1, 2, 3, 4]`. In the first iteration, `number` is assigned the first value from the sequence; in the second iteration, `number` takes the second value; and so on. After the last item in the sequence, the loop terminates, and execution resumes normally with the code after the loop.

Iterating over a range

We often need to iterate over a range of numbers, and it would be quite tedious to have to do so by hard coding the list somewhere. In such cases, the `range()` function comes to the rescue. Let us see the equivalent of the previous snippet of code:

```
# simple.for.py
for number in range(5):
    print(number)
```

The `range()` function is used extensively to create sequences in Python programs. You can call it with a single value, which acts as `stop` (counting will start from `0`). You can also pass two values (`start` and `stop`), or even three (`start`, `stop`, and `step`). Check out the following example:

```
>>> list(range(10))  # one value: from 0 to value (excluded)
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
>>> list(range(3, 8))  # two values: from start to stop (excluded)
[3, 4, 5, 6, 7]
>>> list(range(-10, 10, 4))  # three values: step is added
[-10, -6, -2, 2, 6]
```

For the moment, ignore that we need to wrap `range(...)` within a list. We will explain the reasons for this in *Chapter 5*, *Comprehensions and Generators*. You can see that the behavior is analogous to slicing (which we described in the previous chapter): `start` is included, `stop` is excluded, and you can add an optional `step` parameter, which by default is `1`.

Try modifying the parameters of the `range()` call in our `simple.for.py` code and see what it prints.

Iterating over a sequence

We now have all the tools to iterate over a sequence, so let us build on that example:

```
# simple.for.2.py
surnames = ["Rivest", "Shamir", "Adleman"]
for position in range(len(surnames)):
    print(position, surnames[position])
```

The preceding code adds a little bit of complexity to the game. Execution will show this result:

```
$ python simple.for.2.py
0 Rivest
1 Shamir
2 Adleman
```

Let us use the **inside-out** technique to break it down. We start from the innermost part of what we are trying to understand, and we expand outward. So `len(surnames)` is the length of the surnames list: 3. Therefore, `range(len(surnames))` is actually transformed into `range(3)`. This gives us the range `[0, 3)`, which is the sequence `(0, 1, 2)`. This means that the `for` loop will run for three iterations. In the first one, `position` will take the value `0`, while in the second one, it will take the value `1`, and the value `2` in the third and final iteration. Here, `(0, 1, 2)` represents the possible indexing positions for the `surnames` list. At position `0`, we find `"Rivest"`; at position `1`, `"Shamir"`; and at position 2, `"Adleman"`. If you are curious about what these three men created together, change `print(position, surnames[position])` to `print(surnames[position][0], end="")`, add a final `print()` outside of the loop, and run the code again.

Now, this style of looping is much closer to languages such as Java or C. In Python, it is quite rare to see code like this. You can just iterate over any sequence or collection, so there is no need to get the list of positions and retrieve elements from a sequence at each iteration. Let us change the example into a more Pythonic form:

```
# simple.for.3.py
surnames = ["Rivest", "Shamir", "Adleman"]
for surname in surnames:
    print(surname)
```

The `for` loop can iterate over the `surnames` list, and it gives back each element in order at each iteration. Running this code will print the three surnames, one at a time, which is much easier to read.

However, what if you wanted to print the position as well? Or what if you needed it? Should you go back to the `range(len(...))` form? No. You can use the `enumerate()` built-in function, like this:

```
# simple.for.4.py
surnames = ["Rivest", "Shamir", "Adleman"]
for position, surname in enumerate(surnames):
    print(position, surname)
```

This code is quite interesting as well. Notice that `enumerate()` gives back a two-tuple `(position, surname)` at each iteration, but still, it is more readable (and more efficient) than the `range(len(...))` example. You can call `enumerate()` with a `start` parameter, such as `enumerate(iterable, start)`, and it will start from `start`, rather than `0`. Just another little thing that shows you how much thought has been given to designing Python so that it makes your life easier.

You can use a `for` loop to iterate over lists, tuples, and, in general, anything that Python calls **iterable**. This is an important concept, so let us discuss it in more detail.

Iterators and iterables

According to the Python documentation (`https://docs.python.org/3.12/glossary.html#term-iterable`), an **iterable** is:

> *An object capable of returning its members one at a time. Examples of iterables include all sequence types (such as list, str, and tuple) and some non-sequence types like dict, file objects.*

Simply put, what happens when you write `for k in sequence: ... body ...` is that the `for` loop asks `sequence` for the next element, gets something back, calls that something `k`, and then executes its body. Then, once again, the `for` loop asks `sequence` for the next element, calls it `k` again, executes the body again, and so on, until the sequence is exhausted. Empty sequences will result in zero executions of the body.

Some data structures, when iterated over, produce their elements in order, such as lists, tuples, dictionaries, and strings, while others, such as sets, do not. Python gives us the ability to iterate over iterables, using a type of object called an **iterator**, which is an object that represents a stream of data.

In practice, the whole iterable/iterator mechanism is hidden behind the code. Unless you need to code your own iterable or iterator for some reason, you will not have to worry about this too much. However, it is important to understand how Python handles this key aspect of control flow because it shapes the way in which we write code.

We are going to cover iteration in more detail in *Chapter 5*, *Comprehensions and Generators*, and *Chapter 6*, *OOP, Decorators, and Iterators*.

Iterating over multiple sequences

Let us see another example of how to iterate over two sequences of the same length and work on their respective elements in pairs. Say we have a list of people's names and a second list of numbers representing their ages. We want to print the pair person/age on one line for each of them. Let us start with an example, which we will refine gradually:

```
# multiple.sequences.py
people = ["Nick", "Rick", "Roger", "Syd"]
ages = [23, 24, 23, 21]
for position in range(len(people)):
    person = people[position]
    age = ages[position]
    print(person, age)
```

By now, this code should be straightforward. We iterate over the list of positions (`0`, `1`, `2`, `3`) because we want to retrieve elements from two different lists. Executing it, we get the following:

```
$ python multiple.sequences.py
Nick 23
Rick 24
Roger 23
Syd 21
```

The code works, but it is not very Pythonic. It is cumbersome to have to get the length of `people`, construct a `range`, and then iterate over that. For some data structures, it may also be expensive to retrieve items by their position. It would be better if we could iterate over the sequences directly, as we do for a single sequence. Let us try to improve it by using `enumerate()`:

```
# multiple.sequences.enumerate.py
people = ["Nick", "Rick", "Roger", "Syd"]
ages = [23, 24, 23, 21]
for position, person in enumerate(people):
    age = ages[position]
    print(person, age)
```

That is better, but still not perfect. We are iterating properly on `people`, but we are still fetching `age` using positional indexing, which we want to lose as well. We can achieve that by using the `zip()` function, which we encountered in the previous chapter. Let us use it:

```
# multiple.sequences.zip.py
people = ["Nick", "Rick", "Roger", "Syd"]
ages = [23, 24, 23, 21]
for person, age in zip(people, ages):
    print(person, age)
```

That is much more elegant than the original version. When the `for` loop asks `zip(sequenceA, sequenceB)` for the next element, it gets back a tuple, which is unpacked into `person` and `age`. The tuple will have as many elements as the number of sequences we feed to the `zip()` function. Let us expand a little on the previous example:

```
# multiple.sequences.unpack.py
people = ["Nick", "Rick", "Roger", "Syd"]
ages = [23, 24, 23, 21]
instruments = ["Drums", "Keyboards", "Bass", "Guitar"]
for person, age, instrument in zip(people, ages, instruments):
    print(person, age, instrument)
```

In the preceding code, we added the `instruments` list. Now that we feed three sequences to the `zip()` function, the `for` loop gets back a *three-tuple* at each iteration. The elements of the tuple are unpacked and assigned to `person`, `age`, and `instrument`. Notice that the position of the elements in the tuple respects the position of the sequences in the `zip()` call. Executing the code will yield the following result:

```
$ python multiple.sequences.unpack.py
Nick 23 Drums
Rick 24 Keyboards
Roger 23 Bass
Syd 21 Guitar
```

Note that it is not necessary to unpack the tuples when iterating over multiple sequences like this. You may need to operate on the tuple as a whole within the body of the `for` loop. It is, of course, perfectly possible to do so:

```
# multiple.sequences.tuple.py
people = ["Nick", "Rick", "Roger", "Syd"]
ages = [23, 24, 23, 21]
instruments = ["Drums", "Keyboards", "Bass", "Guitar"]
for data in zip(people, ages, instruments):
    print(data)
```

This is almost identical to the previous example. The difference is that instead of unpacking the tuple we get from `zip(...)`, we assign the entire tuple to `data`.

The while loop

In the preceding pages, we saw the `for` loop in action. It is useful when you need to loop over a sequence or a collection. The key point to keep in mind when you need to decide which looping construct to use is that the `for` loop is best suited in cases where you have to iterate over the elements of a container object or other iterable object.

However, there are other cases when you just need to loop until some condition is satisfied, or even loop indefinitely until the application is stopped. In such cases, we do not have something to iterate on, so the `for` loop would be a poor choice. For situations like this, the `while` loop is more appropriate.

The `while` loop is similar to the `for` loop in that both repeatedly execute a body of instructions. The difference is that the `while` loop does not loop over a sequence. Instead, it loops as long as a certain condition is satisfied. When the condition is no longer satisfied, the loop ends.

As usual, let us see an example that will clarify everything for us. We want to print the binary representation of a positive number. To do so, we can use a simple algorithm that divides by two until we reach zero and collects the remainders. When we reverse the list of remainders we collected, we get the binary representation of the number we started with. For example, if we want a binary representation of the decimal number 6, the steps would be as follows:

1. *6 / 2 = 3* with remainder *0*.
2. *3 / 2 = 1* with remainder *1*.
3. *1 / 2 = 0* with remainder *1*.
4. The list of remainders is *0, 1, 1*.
5. Reversing this, we get *1, 1, 0*, which is also the binary representation of *6*: *110*.

Let us translate this into Python code. We will calculate the binary representation of the number 39, which is 100111:

```
# binary.py
n = 39
remainders = []
while n > 0:
    remainder = n % 2  # remainder of division by 2
    remainders.append(remainder)  # we keep track of remainders
    n //= 2  # we divide n by 2
remainders.reverse()
print(remainders)
```

In the preceding code, we highlighted `n > 0`, which is the condition to keep looping. Notice how the code matches the algorithm we described: as long as `n` is greater than `0`, we divide by `2` and add the remainder to a list. At the end (when `n` has reached `0`), we reverse the list of remainders to get the binary representation of the original value of `n`.

We can use the `divmod()` function to make the code a little shorter (and more Pythonic). The `divmod()` function takes a number and a divisor and returns a tuple, with the result of the integer division and its remainder. For example, `divmod(13, 5)` would return `(2, 3)` and, indeed, *5 * 2 + 3 = 13*.

```
# binary.2.py
n = 39
remainders = []
while n > 0:
    n, remainder = divmod(n, 2)
    remainders.append(remainder)
remainders.reverse()
print(remainders)
```

Now, we reassign `n` to the result of the division by `2` and remainder to the list of remainders in a single line.

The built-in function `bin()` returns a binary representation of a number. So, apart from examples, or as an exercise, there is no need to implement this yourself in Python.

Note that the condition in a `while` loop is a condition to continue looping. If it evaluates to `True`, then the body is executed, another evaluation follows, and so on, until the condition evaluates to `False`. When that happens, the loop stops immediately without executing its body. If the condition never evaluates to `False`, the loop becomes a so-called **infinite loop**. Infinite loops are used, for example, when polling from network devices: you ask the socket whether there is any data, you do something with it if there is any, then you sleep for a small amount of time, and then you ask the socket again, over and over, without ever stopping.

To better illustrate the differences between for and while loops, let us adapt one of the previous examples (`multiple.sequences.py`) using a `while` loop:

```
# multiple.sequences.while.py
people = ["Nick", "Rick", "Roger", "Syd"]
```

```
ages = [23, 24, 23, 21]
position = 0
while position < len(people):
    person = people[position]
    age = ages[position]
    print(person, age)
    position += 1
```

In the preceding code, we have highlighted the *initialization*, *condition*, and *update* of the `position` variable, which makes it possible to simulate the equivalent `for` loop code by handling the iteration manually. Everything that can be done with a `for` loop can also be done with a `while` loop, even though you can see there is a bit of boilerplate you have to go through to achieve the same result. The opposite is also true, but unless you have a reason to do so, you ought to use the right tool for the job.

To recap, use a `for` loop when you need to iterate over an iterable, and use a `while` loop when you need to loop according to whether a condition is satisfied or not. If you keep in mind the difference between the two purposes, you will never choose the wrong looping construct.

Let us now see how to alter the normal flow of a loop.

The break and continue statements

There are scenarios where you will need to alter the regular flow of a loop. You can either skip a single iteration (as many times as you want), or you can break out of the loop entirely. A common use case for skipping iterations is, for example, when you are iterating over a list of items, but you only need to work on those that satisfy some condition. On the other hand, if you are iterating over a collection to search for an item that meets some requirement, you may want to break out of the loop as soon as you find what you are looking for. There are countless possible scenarios; let us work through a couple of examples together to show you how this works in practice.

Suppose that you want to apply a 20% discount on all products that have an expiration date of today. You can achieve this by using the `continue` statement, which tells the looping construct (`for` or `while`) to stop executing the body immediately and go to the next iteration, if any:

```
# discount.py
from datetime import date, timedelta
today = date.today()
tomorrow = today + timedelta(days=1)  # today + 1 day is tomorrow
products = [
```

```
    {"sku": "1", "expiration_date": today, "price": 100.0},
    {"sku": "2", "expiration_date": tomorrow, "price": 50},
    {"sku": "3", "expiration_date": today, "price": 20},
]
for product in products:
    print("Processing sku", product["sku"])
    if product["expiration_date"] != today:
        continue
    product["price"] *= 0.8  # equivalent to applying 20% discount
    print("Sku", product["sku"], "price is now", product["price"])
```

We start by importing the `date` and `timedelta` objects, and then we set up our products. Those with `sku` `1` and `3` have an expiration date of `today`, which means that we want to apply a 20% discount on them. We loop over each `product` and inspect the expiration date. If the expiration date does not match `today`, we do not want to execute the rest of the body, so we execute the `continue` statement. Execution of the loop body stops and goes on to the next iteration. If we run the `discount.py` module, this is the output:

```
$ python discount.py
Processing sku 1
Sku 1 price is now 80.0
Processing sku 2
Processing sku 3
Sku 3 price is now 16.0
```

As you can see, the last two lines of the body have not been executed for `sku` number 2.

Let us now see an example of breaking out of a loop. Say we want to tell whether at least one of the elements in a list evaluates to `True` when fed to the `bool()` function. Given that we need to know whether there is at least one, when we find it, we do not need to keep scanning the list any further. In Python code, this translates to using the `break` statement. Let us write this down into code:

```
# any.py
items = [0, None, 0.0, True, 0, 7]  # True and 7 evaluate to True
found = False  # this is called a "flag"
for item in items:
    print("scanning item", item)
    if item:
        found = True  # we update the flag
```

```
        break
if found:  # we inspect the flag
    print("At least one item evaluates to True")
else:
    print("All items evaluate to False")
```

The preceding code makes use of a common programming pattern; you set up a **flag** variable before starting the inspection of the items. If you find an element that matches your criteria (in this example, that evaluates to `True`), you update the flag and stop iterating. After iteration, you inspect the flag and act accordingly. Execution yields:

```
$ python any.py
scanning item 0
scanning item None
scanning item 0.0
scanning item True
At least one item evaluates to True
```

See how execution stopped after `True` was found? The `break` statement is similar to `continue`, in that it immediately stops executing the body of the loop, but it also prevents any further iterations from running, effectively breaking out of the loop.

There is no need to write code to detect whether there is at least one element in a sequence that evaluates to `True`, as the built-in function `any()` does exactly this.

You can use as many `continue` or `break` statements as you need, anywhere in a loop body (`for` or `while`). You can even use both in the same loop.

A special else clause

One of the features we have seen only in the Python language is the ability to have an `else` clause after a loop. It is very rarely used, but it is useful to have. If the loop ends normally, because of exhaustion of the iterator (`for` loop) or because the condition is finally not met (`while` loop), then the `else` suite (if present) is executed. If execution is interrupted by a `break` statement, the `else` clause is not executed.

Let us take an example of a `for` loop that iterates over a group of items, looking for one that would match some condition. If we do not find at least one that satisfies the condition, we want to raise an **exception**. This means that we want to arrest the regular execution of the program and signal that there was an error, or exception. Exceptions will be the subject of *Chapter 7, Exceptions and Context Managers*, so do not worry if you do not fully understand them for now. Just bear in mind that they alter the regular flow of the code.

Let us first see how we would do this without the `for...else` syntax. Say that we want to find, among a collection of people, one that could drive a car:

```
# for.no.else.py
class DriverException(Exception):
    pass
people = [("James", 17), ("Kirk", 9), ("Lars", 13), ("Robert", 8)]
driver = None
for person, age in people:
    if age >= 18:
        driver = (person, age)
        break
if driver is None:
    raise DriverException("Driver not found.")
```

Notice the *flag* pattern again. We set the driver to be `None`, and then if we find one, we update the `driver` flag. At the end of the loop, we inspect it to see whether one was found. Notice that if a driver is not found, `DriverException` is raised, signaling to the program that execution cannot continue (we are lacking the driver).

Now, let us see how to do this with an `else` clause on the `for` loop:

```
# for.else.py
class DriverException(Exception):
    pass
people = [("James", 17), ("Kirk", 9), ("Lars", 13), ("Robert", 8)]
for person, age in people:
    if age >= 18:
        driver = (person, age)
        break
else:
    raise DriverException("Driver not found.")
```

Notice that we no longer need the *flag* pattern. The exception is raised as part of the loop logic, which makes good sense because the loop checks for some condition. All we need to do is set up a `driver` object in case we find one; this way the rest of the code uses the `driver` object for further processing. Notice that the code is shorter and more elegant because the logic is now correctly grouped together, where it belongs.

In his *Transforming Code into Beautiful, Idiomatic Python* video, Raymond Hettinger suggests a much better name for the `else` statement associated with a `for` loop: `nobreak`. If you struggle with remembering how the `else` works for a `for` loop, simply remembering this fact should help you.

Assignment expressions

Before we look at some more complicated examples, we would like to briefly introduce you to a feature that was added to the language in Python 3.8, via PEP 572 (`https://peps.python.org/pep-0572`). Assignment expressions allow us to bind a value to a name in places where normal assignment statements are not allowed. Instead of the normal assignment operator `=`, assignment expressions use `:=` (known as the **walrus operator** because it resembles the eyes and tusks of a walrus).

Statements and expressions

To understand the difference between normal assignments and assignment expressions, we need to understand the difference between statements and expressions. According to the Python documentation (`https://docs.python.org/3.12/glossary.html#term-statement`), a **statement** is:

> *...part of a suite (a "block" of code). A statement is either an expression or one of several constructs with a keyword, such as* `if`*,* `while` *or* `for`*.*

An **expression**, on the other hand, is:

> *A piece of syntax which can be evaluated to some value. In other words, an expression is an accumulation of expression elements like literals, names, attribute access, operators or function calls which all return a value.*

The key distinguishing feature of an expression is that it has a value. Notice that an expression can be a statement, but not all statements are expressions. In particular, assignments like `name = "heinrich"` are not expressions, so they do not have a value. This means that you cannot use an assignment statement in the condition expression of a `while` loop or `if` statement (or any other place where a value is required).

This explains why the Python console does not print a value when you assign a value to a name. For example:

```
>>> name = "heinrich"
>>>
```

is a statement, which does not have a return value to print.

Using the walrus operator

Without assignment expressions, you would have to use two separate statements if you wanted to bind a value to a name and use that value in an expression. For example, it is quite common to see code like:

```
# walrus.if.py
remainder = value % modulus
if remainder:
    print(f"Not divisible! The remainder is {remainder}.")
```

With assignment expressions, we could rewrite this as:

```
# walrus.if.py
if remainder := value % modulus:
    print(f"Not divisible! The remainder is {remainder}.")
```

Assignment expressions allow us to write fewer lines of code. Used with care, they can also lead to cleaner, more understandable code. Let us look at a slightly bigger example to see how an assignment expression can simplify a `while` loop.

In interactive scripts, we often need to ask a user to choose between a number of options. For example, suppose we are writing an interactive script that allows customers at an ice cream shop to choose what flavor they want. To avoid confusion when preparing orders, we want to ensure that the user chooses one of the available flavors. Without assignment expressions, we might write something like this:

```
# menu.no.walrus.py
flavors = ["pistachio", "malaga", "vanilla", "chocolate"]
prompt = "Choose your flavor: "
print(flavors)
while True:
    choice = input(prompt)
    if choice in flavors:
        break
    print(f"Sorry, '{choice}' is not a valid option.")
print(f"You chose '{choice}'.")
```

Take a moment to read this code carefully. Note the condition on the loop: `while True` means "loop forever," which is not what we want. We want to stop the loop when the user inputs a valid flavor (`choice in flavors`). To achieve that, we have an `if` statement and a `break` inside the loop. The logic to control the loop is not immediately obvious. Despite that, this is actually quite a common pattern when the value needed to control the loop can only be obtained inside it.

The `input()` function is very useful in interactive scripts. It prompts the user for input and returns it as a string.

How can we improve on this? Let us try to use an assignment expression:

```
# menu.walrus.py
flavors = ["pistachio", "malaga", "vanilla", "chocolate"]
prompt = "Choose your flavor: "
print(flavors)
while (choice := input(prompt)) not in flavors:
    print(f"Sorry, '{choice}' is not a valid option.")
print(f"You chose '{choice}'.")
```

Now, the loop conditional says exactly what we want. That is much easier to understand. The code is also three lines shorter.

We need parentheses around the assignment expression in this example because the `:=` operator has lower precedence than the `not in` operator. Try removing them and see what happens.

We have seen examples of using assignment expressions in `if` and `while` statements. Besides these use cases, assignment expressions are also useful in *lambda expressions* (which you will meet in *Chapter 4*, *Functions, the Building Blocks of Code*), as well as *comprehensions* and *generators* (which you will learn about in *Chapter 5*, *Comprehensions and Generators*).

A word of warning

The introduction of the walrus operator in Python was somewhat controversial. Some people feared that it would make it too easy to write ugly, non-Pythonic code. We think that these fears are not entirely justified. As you saw above, the walrus operator can *improve* code and make it easier to read. Like any powerful feature, it can, however, be abused to write *obfuscated* code. We would advise you to use it sparingly. Always think carefully about how it impacts the readability of your code.

Putting all this together

Now that we have covered the basics of conditionals and loops, we can move on to the example programs we promised at the beginning of this chapter. We will mix and match here so that you can see how you can use all these concepts together.

A prime generator

Let us start by writing some code to generate a list of prime numbers up to (and including) some limit. Please bear in mind that we are going to write a very inefficient and rudimentary algorithm to find prime numbers. The important thing is to concentrate on those bits in the code that belong to this chapter's subject.

According to Wolfram MathWorld:

> *A* **prime number** *(or prime integer, often simply called a "***prime***" for short) is a positive integer p>1 that has no positive integer divisors other than 1 and p itself. More concisely, a prime number p is a positive integer having exactly one positive divisor other than 1, meaning it is a number that cannot be factored.*

Based on this definition, if we consider the first 10 natural numbers, we can see that 2, 3, 5, and 7 are primes, while 1, 4, 6, 8, 9, and 10 are not. To determine whether a number, *N*, is prime, you can divide it by each of the natural numbers in the range *[2, N)*. If the remainder of any division is zero, then the number is not a prime.

To generate the sequence of prime numbers, we will consider each natural number, starting from two, up to the limit, and test whether it is a prime. We will write two versions of this, the second of which will exploit the `for...else` syntax:

```
# primes.py
primes = []  # this will contain the primes at the end
upto = 100  # the limit, inclusive
for n in range(2, upto + 1):
    is_prime = True  # flag, new at each iteration of outer for
    for divisor in range(2, n):
        if n % divisor == 0:
            is_prime = False
            break
    if is_prime:  # check on flag
        primes.append(n)
print(primes)
```

There is quite a lot happening in this code. We start by setting up an empty `primes` list, which will contain the primes at the end. We set the limit to `100`, and because we want it to be inclusive, we have to iterate over `range(2, upto + 1)` in our outer `for` loop (remember that `range(2, upto)` *would stop at upto - 1*). The outer loop iterates over the candidate primes—that is, all natural numbers from 2 to `upto`. Each iteration of this loop tests one number to determine whether it is a prime. In each iteration of the outer loop, we set up a flag (which is set to `True` at each iteration), and then start dividing the current value of `n` by all numbers from 2 to `n - 1`. If we find a proper divisor for `n`, it means `n` is composite, so we set the flag to `False` and break the loop. Notice that when we break the inner loop, the outer one keeps on going as normal. The reason we break after having found a proper divisor for `n` is that we do not need any further information to be able to tell that `n` is not a prime.

When we check the `is_prime` flag after the inner loop, if it is still `True`, it means we could not find any number in *[2, n)* that is a proper divisor for `n`; therefore, `n` is a prime. We append `n` to the `primes` list and proceed to the next iteration, until `n` equals `100`.

Running this code outputs:

```
$ python primes.py
[2, 3, 5, 7, 11, 13, 17, 19, 23, 29, 31, 37, 41, 43, 47, 53, 59, 61,
67, 71, 73, 79, 83, 89, 97]
```

Before proceeding, we will pose the following question: one of the iterations of the outer loop is different from the rest. Can you tell which iteration this is—and why? Think about it for a moment, go back to the code, try to work it out for yourself, and then keep reading.

Did you find the answer? Do not feel bad if you did not, the skill to understand what the code does by simply looking at it takes time and experience to learn. It is an important skill to have as a programmer though, so try to exercise it whenever you can. We will tell you the answer now: the first iteration behaves differently from all the others. The reason is that in the first iteration, `n` is 2. Therefore, the innermost `for` loop will not run at all because it is a `for` loop that iterates over `range(2, 2)`, which is an empty range. Try it yourself, write a simple `for` loop with that iterable, put a `print` in the body, and see what happens when you run it.

We are not going to try to make this code more efficient from an algorithmic point of view. But let us use some of what we learned in this chapter to at least make it easier to read:

```
# primes.else.py
primes = []
upto = 100
for n in range(2, upto + 1):
    for divisor in range(2, n):
        if n % divisor == 0:
            break
    else:
        primes.append(n)
print(primes)
```

Using an `else` clause on the inner loop allows us to get rid of the `is_prime` flag. Instead, we append `n` to the `primes` list when we know that the inner loop has not encountered any `break` statements. It is only two lines shorter, but the code is simpler, cleaner, and reads better. This is important, as simplicity and readability count for a lot in programming. Always look for ways to simplify your code and make it easier to read. You will thank yourself when you return to it months later and have to try to understand what you did before.

Applying discounts

In this example, we want to show you a technique called a **lookup table**, which we are very fond of. We will start by simply writing some code that assigns a discount to customers based on their coupon value. We will keep the logic down to a minimum here—remember that all we really care about is understanding conditionals and loops:

```
# coupons.py
customers = [
    dict(id=1, total=200, coupon_code="F20"),  # F20: fixed, £20
    dict(id=2, total=150, coupon_code="P30"),  # P30: percent, 30%
    dict(id=3, total=100, coupon_code="P50"),  # P50: percent, 50%
    dict(id=4, total=110, coupon_code="F15"),  # F15: fixed, £15
]
for customer in customers:
    match customer["coupon_code"]:
        case "F20":
            customer["discount"] = 20.0
        case "F15":
            customer["discount"] = 15.0
        case "P30":
            customer["discount"] = customer["total"] * 0.3
        case "P50":
            customer["discount"] = customer["total"] * 0.5
        case _:
            customer["discount"] = 0.0
for customer in customers:
    print(customer["id"], customer["total"], customer["discount"])
```

We start by setting up some customers. They have an order total, a coupon code, and an ID. We made up four types of coupons: two are for fixed amounts and two are percentage-based. We use a `match` statement, with a `case` for each coupon code and a wildcard to handle invalid coupons. We compute the discount and set it as the `"discount"` key in the `customer` dictionary.

Finally, we just print out part of the data to see whether our code works properly:

```
$ python coupons.py
1 200 20.0
2 150 45.0
```

```
3 100 50.0
4 110 15.0
```

This code is simple to understand, but all those `match` cases are cluttering the logic. Adding more coupon codes requires adding additional cases and implementing the discount calculation for each case. The discount calculation is very similar in most cases, which makes the code repetitive and violates the **Don't Repeat Yourself** (**DRY**) principle. In cases like this, you can use a dictionary to your advantage, like this:

```
# coupons.dict.py
customers = [
    dict(id=1, total=200, coupon_code="F20"),  # F20: fixed, £20
    dict(id=2, total=150, coupon_code="P30"),  # P30: percent, 30%
    dict(id=3, total=100, coupon_code="P50"),  # P50: percent, 50%
    dict(id=4, total=110, coupon_code="F15"),  # F15: fixed, £15
]
discounts = {
    "F20": (0.0, 20.0),  # each value is (percent, fixed)
    "P30": (0.3, 0.0),
    "P50": (0.5, 0.0),
    "F15": (0.0, 15.0),
}
for customer in customers:
    code = customer["coupon_code"]
    percent, fixed = discounts.get(code, (0.0, 0.0))
    customer["discount"] = percent * customer["total"] + fixed

for customer in customers:
    print(customer["id"], customer["total"], customer["discount"])
```

Running the preceding code produces exactly the same output as the snippet before it. The code is two lines shorter, but more importantly, we gained a lot in readability, as the body of the `for` loop is now just three lines long and easy to understand. The key idea here is to use a dictionary as a **lookup table**. In other words, we try to fetch something (the parameters for the discount calculation) from the dictionary based on a code (our `coupon_code`). We use `dict.get(key, default)` to ensure that we can handle codes that are not in the dictionary, by supplying a default value.

Aside from readability, another major advantage of this approach is that we can easily add new coupon codes (or remove old ones) without changing the implementation; we only need to change the *data* in the lookup table. In a real-world application, we could even store the lookup table in a database and provide an interface for users to add or remove coupon codes at runtime.

Notice that we had to apply some simple linear algebra to calculate the discount. Each discount has a percentage and fixed part in the dictionary, represented by a two-tuple. By applying `percent * total + fixed`, we get the correct discount. When `percent` is `0`, the formula just gives the fixed amount, and it gives `percent * total` when `fixed` is `0`.

This technique is closely related to **dispatch tables**, which store functions as values in a table. This allows for even greater flexibility. Some object-oriented programming languages use this technique internally to implement features such as virtual methods.

If you are still unclear as to how this works, we suggest you take your time and experiment with it. Change values and add `print()` statements to see what is going on while the program is running.

A quick peek at the itertools module

A chapter about iterables, iterators, conditional logic, and looping would not be complete without a few words about the `itertools` module. According to the Python official documentation (`https://docs.python.org/3.12/library/itertools.html`), the `itertools` module:

> *...implements a number of iterator building blocks inspired by constructs from APL, Haskell, and SML. Each has been recast in a form suitable for Python.*
>
> *The module standardizes a core set of fast, memory efficient tools that are useful by themselves or in combination. Together, they form an "iterator algebra" making it possible to construct specialized tools succinctly and efficiently in pure Python.*

We do not have room here to show you everything this module has to offer, so we encourage you to explore it further for yourself. However, we can promise that you will enjoy it. It provides you with three broad categories of iterators. As an introduction, we shall give you a small example of one iterator taken from each category.

Infinite iterators

Infinite iterators allow you to use a `for` loop as an infinite loop, iterating over a sequence that never ends:

```
# infinite.py
from itertools import count
for n in count(5, 3):
    if n > 20:
        break
    print(n, end=", ") # instead of newline, comma and space
```

Running the code outputs:

```
$ python infinite.py
5, 8, 11, 14, 17, 20,
```

The `count` factory class makes an iterator that simply goes on and on counting. In this example, it starts from `5` and keeps adding `3` at every iteration. We need to break it manually if we do not want to get stuck in an infinite loop.

Iterators terminating on the shortest input sequence

This category is quite interesting. It allows you to create an iterator based on multiple iterators, combining their values according to some logic. The key point here is that the resulting iterator will not break if one of the input iterators is shorter than the rest. It will simply stop as soon as the shortest iterator is exhausted. This may seem rather abstract, so let us give you an example using `compress()`. This iterator takes a sequence of *data* and a sequence of *selectors*, yielding only those values from the data sequence that correspond to `True` values in the selectors sequence. For example, `compress("ABC", (1, 0, 1))` would give back `"A"` and `"C"` because they correspond to `1`. Let us see a simple example:

```
# compress.py
from itertools import compress
data = range(10)
even_selector = [1, 0] * 10
odd_selector = [0, 1] * 10
even_numbers = list(compress(data, even_selector))
odd_numbers = list(compress(data, odd_selector))
```

```
print(odd_selector)
print(list(data))
print(even_numbers)
print(odd_numbers)
```

Notice that `odd_selector` and `even_selector` are 20 elements in length, while `data` is only 10. `compress()` will stop as soon as `data` has yielded its last element. Running this code produces the following:

```
$ python compress.py
[0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1]
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
[0, 2, 4, 6, 8]
[1, 3, 5, 7, 9]
```

It is a fast and convenient way of selecting elements out of an iterable. The code is simple, but notice that instead of using a `for` loop to iterate over each value that is given back by the `compress()` calls, we used `list()`, which does the same, but instead of executing a body of instructions, it puts all the values into a list and returns it.

Combinatoric generators

The third category of iterators from `itertools` is combinatoric generators. Let us look at a simple example of permutations. According to Wolfram MathWorld:

> *A permutation, also called an "arrangement number" or "order," is a rearrangement of the elements of an ordered list S into a one-to-one correspondence with S itself.*

For example, there are six permutations of `ABC`: `ABC`, `ACB`, `BAC`, `BCA`, `CAB`, and `CBA`.

If a set has *N* elements, then the number of permutations of them is *N!* (*N* factorial). For example, the string `ABC` has *3! = 3 * 2 * 1 = 6* permutations. Let us see this in Python:

```
# permutations.py
from itertools import permutations
print(list(permutations("ABC")))
```

This short snippet of code produces the following result:

```
$ python permutations.py
[('A', 'B', 'C'), ('A', 'C', 'B'), ('B', 'A', 'C'), ('B', 'C', 'A'),
('C', 'A', 'B'), ('C', 'B', 'A')]
```

Be careful when you play with permutations. Their number grows at a rate that is proportional to the factorial of the number of elements you are permuting, and that number can get really big, really fast.

There is a third-party library that expands on the `itertools` module, called `more-itertools`. You can find its documentation at `https://more-itertools.readthedocs.io/`.

Summary

In this chapter, we have taken another step toward expanding our Python vocabulary. We have seen how to drive the execution of code by evaluating conditions, along with how to loop and iterate over sequences and collections of objects. This gives us the power to control what happens when our code is run, which means we get an idea of how to shape it so that it does what we want, having it react to data that changes dynamically.

We have also seen how to combine everything together in a couple of simple examples, and finally, we took a brief look at the `itertools` module, which is full of interesting iterators that can enrich our abilities with Python to a greater degree.

Now, it is time to switch gears, take another step forward, and talk about functions. The next chapter is all about them, and they are extremely important. Make sure you are comfortable with what has been covered so far. We want to provide you with interesting examples, so let's go.

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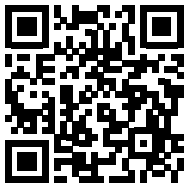

4

Functions, the Building Blocks of Code

> *"To create architecture is to put in order. Put what in order? Functions and objects."*
>
> *—Le Corbusier*

In the previous chapters, we have seen that everything is an object in Python, and functions are no exception. But what exactly is a function? A function is *a block of reusable code designed to perform a specific task or a related group of tasks*. This unit can then be imported and used wherever it is needed. There are many advantages to using functions in your code, as we will see shortly.

In this chapter, we are going to cover the following:

- Functions—what they are and why we should use them
- Scopes and name resolution
- Function signatures—input parameters and return values
- Recursive and anonymous functions
- Importing objects for code reuse

We believe the saying *a picture is worth a thousand words* is particularly true when explaining functions to someone who is new to this concept, so please take a look at the following figure:

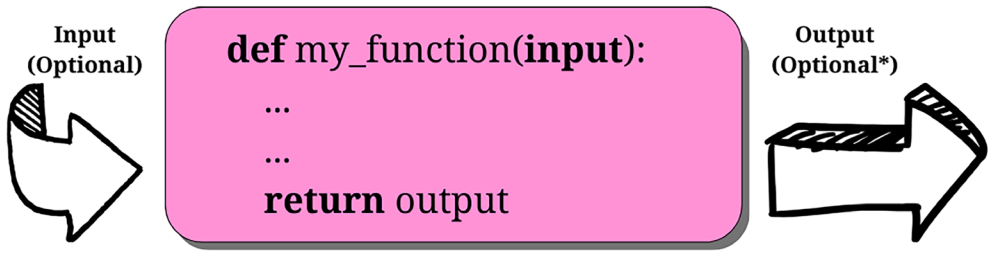

Figure 4.1: An example of a function

As you can see, a function is a block of instructions, packaged as a whole, like a box. Functions can accept input parameters and produce output values. Both of these are optional, as we will see in the examples in this chapter.

A function in Python is defined using the `def` keyword, after which the name of the function follows, terminated by a pair of parentheses (which may or may not contain input parameters); a colon (`:`) then signals the end of the function definition. Immediately afterward, indented by four spaces, we find the body of the function, which is the set of instructions that the function will execute when called.

Note that the indentation by four spaces is not mandatory, but it is the number of spaces suggested by PEP 8, and, in practice, it is the most widely used spacing measure.

A function may or may not return an output. If a function wants to return an output, it does so by using the `return` keyword, followed by the desired output. You may have noticed the little * after *Optional* in the output section of the preceding diagram. This is because a function always returns something in Python, even if you do not explicitly use the `return` statement. If the function has no `return` statement in its body, or no value is given to the `return` statement itself, the function returns `None`.

This design choice is rooted in several reasons, the most important of which are:

- **Simplicity and consistency**: Whether the function is explicitly returning a value or not, its behavior is consistent.
- **Complexity reduction**: Several languages make a distinction between functions (which return a value) and **procedures** (which do not). Functions in Python can act as both, with no need for separate constructs. This minimizes the number of concepts a programmer must learn.

- **Consistency for multiple pathways**: Functions with multiple conditional branches will return `None` when no other return statement is executed. `None`, therefore, is a useful default value.

The list provided demonstrates the multitude of factors that can influence an apparently simple design decision. It is the careful and deliberate choices underpinning Python's design that contribute to its elegance, simplicity, and versatility.

Why use functions?

Functions are among the most important concepts and constructs of any language, so let us give you a few reasons why we need them:

- They reduce code duplication in a program. Encapsulating the instructions for a task in a function that we can import and call whenever we want allows us to avoid duplicating the implementation.
- They help in splitting a complex task or procedure into smaller blocks, each of which becomes a function.
- They hide the implementation details from their users.
- They improve traceability.
- They improve readability.

Let us now look at a few examples to get a better understanding of each point.

Reducing code duplication

Imagine that you are writing a piece of scientific software, and you need to calculate prime numbers up to a certain limit—as we did in the previous chapter. You have an algorithm to calculate them, so you copy it and paste it to wherever you need to use it. One day, though, a colleague gives you a more performant algorithm to calculate primes. At this point, you need to go over your whole code base and replace the old code with the new one.

This procedure is quite error-prone. You can easily remove parts of the surrounding code by mistake or fail to remove some of the code you meant to replace. You also risk missing some of the places where the prime calculation is done, leaving your software in an inconsistent state where the same action is performed in different ways. What if, instead of replacing code with a better version of it, you need to fix a bug and you miss a spot. That would be even worse. What if the names of the variables in the old algorithm are different from those used in the new one? That will also complicate things.

To avoid all that, you write a function, `get_prime_numbers(upto)`, and use it anywhere you need to calculate a list of primes. When your colleague gives you a better implementation, all you need to do is replace the body of that function with the new code. The rest of the software will automatically adapt since it is just calling the function.

Your code will be shorter and free from inconsistencies between old and new ways of performing a task. You are also less likely to leave behind undetected bugs that arise from copy-and-paste failures or oversights.

Splitting a complex task

Functions are also useful for splitting long or complex tasks into smaller ones. The result is that the code benefits from it in several ways, including readability, testability, and reusability.

To give you a simple example, imagine that you are preparing a report. Your code needs to fetch data from a data source, parse it, filter it, and polish it, and then a whole series of algorithms needs to be run against it, to produce the results that will be written into the report. It is common to see procedures like this that are just one big `do_report(data_source)` function. There might be hundreds of lines of code that run before we finally produce the report.

Inexperienced programmers, not well versed in the art of crafting simple, well structured code, may produce functions with hundreds of lines of code. They are hard to follow through, to find the places where things are changing context (such as finishing one task and starting the next one). Let us show you a better approach instead:

```
# data.science.example.py
def do_report(data_source):
    # fetch and prepare data
    data = fetch_data(data_source)
    parsed_data = parse_data(data)
    filtered_data = filter_data(parsed_data)
    polished_data = polish_data(filtered_data)

    # run algorithms on data
    final_data = analyse(polished_data)

    # create and return report
    report = Report(final_data)
    return report
```

The previous example is fictitious, of course, but can you see how easy it would be to go through the code? If the end result looks wrong, it would be easy to debug each of the single data outputs in the `do_report()` function. Moreover, it is even easier to exclude part of the process temporarily from the whole procedure (you just need to comment out the parts that you need to suspend). Code like this is easier to deal with.

Hiding implementation details

Let us stay with the preceding example to talk about this point as well. We can see that, by going through the code of the `do_report()` function, we can get a surprisingly good understanding without reading one single line of implementation. This is because functions hide the implementation details.

This feature means that, if we do not need to delve into the details, we are not forced to, in the way that we would be if `do_report()` was just one big, long function. To understand what was going on, we would have to read and understand every single line of its code. When it is broken down into smaller functions, we do not necessarily need to read every line of every one of them to understand what the code does. This reduces the time we spend reading the code and, since in a professional environment reading code takes much more time than writing it, it is important to reduce it to a minimum.

Improving readability

Programmers sometimes do not see the point in writing a function with a body of one or two lines of code, so let us look at an example that shows you why you should probably still do it.

Imagine that you need to multiply two matrices, like in the example below:

$$\begin{pmatrix} 1 & 2 \\ 3 & 4 \end{pmatrix} \cdot \begin{pmatrix} 5 & 1 \\ 2 & 1 \end{pmatrix} = \begin{pmatrix} 9 & 3 \\ 23 & 7 \end{pmatrix}$$

Would you prefer to have to read this code:

```
# matrix.multiplication.nofunc.py
a = [[1, 2], [3, 4]]
b = [[5, 1], [2, 1]]
c = [
    [sum(i * j for i, j in zip(r, c)) for c in zip(*b)] for r in a
]
```

Or, would you prefer this:

```
# matrix.multiplication.func.py
def matrix_mul(a, b):
    return [
        [sum(i * j for i, j in zip(r, c)) for c in zip(*b)]
        for r in a
    ]
a = [[1, 2], [3, 4]]
b = [[5, 1], [2, 1]]
c = matrix_mul(a, b)
```

It is much easier to understand that `c` is the result of the multiplication of `a` and `b` in the second example, and it is much easier to read the code. If we do not need to modify that multiplication logic, we do not even need to go into the implementation details of `matrix_mul()`. Therefore, readability is improved here while, in the first snippet, we would have to spend time trying to understand what that complicated list comprehension is doing.

Do not worry if you do not understand list comprehensions, as we will study them in *Chapter 5*, *Comprehensions and Generators*.

Improving traceability

Imagine that we have written some code for an e-commerce website. We display the product prices on several pages. Imagine that the prices in the database are stored with no VAT (sales tax), but we want to display them on the website with VAT at 20%. Here are a few ways of calculating the VAT-inclusive price from the VAT-exclusive price:

```
# vat.nofunc.py
price = 100  # GBP, no VAT
final_price1 = price * 1.2
final_price2 = price + price / 5.0
final_price3 = price * (100 + 20) / 100.0
final_price4 = price + price * 0.2
```

These four different ways of calculating a VAT-inclusive price are all perfectly acceptable; we have encountered all of them in the professional code that we have worked on over the years.

Now, imagine that we start selling products in different countries, and some of them have different VAT rates, so we need to refactor the code (throughout the website) in order to make that VAT calculation dynamic.

How do we trace all the places in which we are performing a VAT calculation? Coding today is a collaborative task and we cannot be sure that the VAT has been calculated using only one of those forms. It is going to be difficult.

So, let us write a function that takes the input values `vat` and `price` (VAT-exclusive) and returns a VAT-inclusive price:

```
# vat.function.py
def calculate_price_with_vat(price, vat):
    return price * (100 + vat) / 100
```

Now we can import that function and use it in any place on the website where we need to calculate a VAT-inclusive price, and when we need to trace those calls, we can search for `calculate_price_with_vat`.

Note that, in the preceding example, `price` is assumed to be VAT-exclusive, and `vat` is a percentage value (for example, 19, 20, or 23).

Scopes and name resolution

In *Chapter 1*, *A Gentle Introduction to Python*, we discussed scopes and namespaces. We are going to expand on that concept now. Finally, we can talk in terms of functions, and this will make everything easier to understand. Let us start with a simple example:

```
# scoping.level.1.py
def my_function():
    test = 1  # this is defined in the local scope of the function
    print("my_function:", test)

test = 0  # this is defined in the global scope
my_function()
print("global:", test)
```

We defined the `test` name in two different places in the previous example—it is actually in two different scopes. One is the global scope (`test = 0`), and the other is the local scope of the `my_function()` function (`test = 1`). If we execute the code, we will see this:

```
$ python scoping.level.1.py
my_function: 1
global: 0
```

It is clear that `test = 1` shadows the `test = 0` assignment in `my_function()`. In the global context, `test` is still `0`, as you can see from the output of the program, but we define the `test` name again in the function body, and we set it to point to the integer `1`. Both of the `test` names therefore exist: one in the global scope, pointing to an int object with a value of `0`, and the other in the `my_function()` scope, pointing to an `int` object with a value of `1`. Let us comment out the line with `test = 1`. Python searches for the `test` name in the next enclosing namespace (recall the **LEGB** rule: **local**, **enclosing**, **global**, **built-in**, described in *Chapter 1*, *A Gentle Introduction to Python*) and, in this case, we will see the value `0` printed twice. Try it in your code.

Now, let us give you a more complex example with nested functions:

```
# scoping.level.2.py
def outer():
    test = 1  # outer scope

    def inner():
        test = 2  # inner scope
        print("inner:", test)

    inner()
    print("outer:", test)

test = 0  # global scope
outer()
print("global:", test)
```

In the preceding code, we have two levels of shadowing. One level is in the `outer()` function, and the other one is in the `inner()` function.

If we run the code, we get:

```
$ python scoping.level.2.py
inner: 2
outer: 1
global: 0
```

Try commenting out the `test = 1` line. Can you figure out what the result will be? When reaching the `print('outer:', test)` line, Python will have to look for `test` in the next enclosing scope; therefore it will find and print `0`, instead of `1`. Make sure you comment out `test = 2` as well, to see whether you understand what happens and whether the LEGB rule is clear to you, before proceeding.

Another thing to note is that Python gives us the ability to define a function in another function. The `inner()` function's name is defined within the namespace of the `outer()` function, exactly as would happen with any other name.

The global and nonlocal statements

In the preceding example, we can alter what happens to the shadowing of the test name by using one of these two special statements: `global` and `nonlocal`. As you can see, when we define `test = 2` in the `inner()` function, we do not overwrite `test` in the `outer()` function or in the global scope.

We can get read access to those names if we use them in a nested scope that does not define them, but we cannot modify them because when we write an assignment instruction, we are actually defining a new name in the current scope.

We can use the `nonlocal` statement to change this behavior. According to the official documentation:

> *"The* `nonlocal` *statement causes the listed identifiers to refer to previously bound variables in the nearest enclosing scope excluding globals."*

Let us introduce it in the `inner()` function and see what happens:

```
# scoping.level.2.nonlocal.py
def outer():
    test = 1  # outer scope

    def inner():
```

```
        nonlocal test
        test = 2  # nearest enclosing scope (which is 'outer')
        print("inner:", test)

    inner()
    print("outer:", test)

test = 0  # global scope
outer()
print("global:", test)
```

Notice how in the body of the `inner()` function we have declared the `test` name to be `nonlocal`. Running this code produces the following result:

```
$ python scoping.level.2.nonlocal.py
inner: 2
outer: 2
global: 0
```

By declaring `test` to be `nonlocal` in the `inner()` function, we actually bind the `test` name to the one declared in the `outer` function. If we removed the `nonlocal test` line from the `inner()` function and tried it inside the `outer()` function, we would get a `SyntaxError`, because the `nonlocal` statement works on enclosing scopes, but not in the global one.

Is there a way to get write access to that `test = 0` in the global namespace? Yes, we just need to use the `global` statement:

```
# scoping.level.2.global.py
def outer():
    test = 1  # outer scope

    def inner():
        global test
        test = 2  # global scope
        print("inner:", test)

    inner()
    print("outer:", test)

test = 0  # global scope
```

```
outer()
print("global:", test)
```

Note that we have now declared the `test` name to be `global`, which will bind it to the one we defined in the global namespace (`test = 0`). Run the code and you should get the following:

```
$ python scoping.level.2.global.py
inner: 2
outer: 1
global: 2
```

This shows that the name affected by the `test = 2` assignment is now the one in the `global` scope. This would also work in the `outer()` function because, in this case, we are referring to the global scope.

Try it for yourself and see what changes. Spend some time to get comfortable with scopes and name resolution—it is very important. As a bonus question, can you tell what would happen if you defined `inner()` outside `outer()` in the preceding examples?

Input parameters

At the beginning of this chapter, we saw that a function can take input parameters. Before we delve into all the possible types of parameters, let us make sure you have a clear understanding of what passing an argument to a function means. There are three key points to keep in mind:

- Argument-passing is nothing more than assigning an object to a local variable name
- Assigning an object to an argument name inside a function does not affect the caller
- Changing a mutable object argument in a function does affect the caller

Before we explore the topic of arguments any further, please allow us to clarify the terminology a little. According to the official Python documentation:

> *"Parameters are defined by the names that appear in a function definition, whereas arguments are the values actually passed to a function when calling it. Parameters define what types of arguments a function can accept."*

We will try to be precise when referring to parameters and arguments, but it is worth noting that they are sometimes used synonymously as well. Let us now look at some examples.

Argument-passing

Take a look at the following code. We declare a name, `x`, in the global scope, then we declare a function, `func(y)`, and finally, we call it, passing `x`:

```
# key.points.argument.passing.py
x = 3
def func(y):
    print(y)

func(x)  # prints: 3
```

When `func()` is called with `x`, within its local scope, a name, `y`, is created, and it is pointed to the same object that `x` is pointing to. This is better clarified in *Figure 4.2* (do not worry about the fact that this example was run with Python 3.11—this is a feature that has not changed).

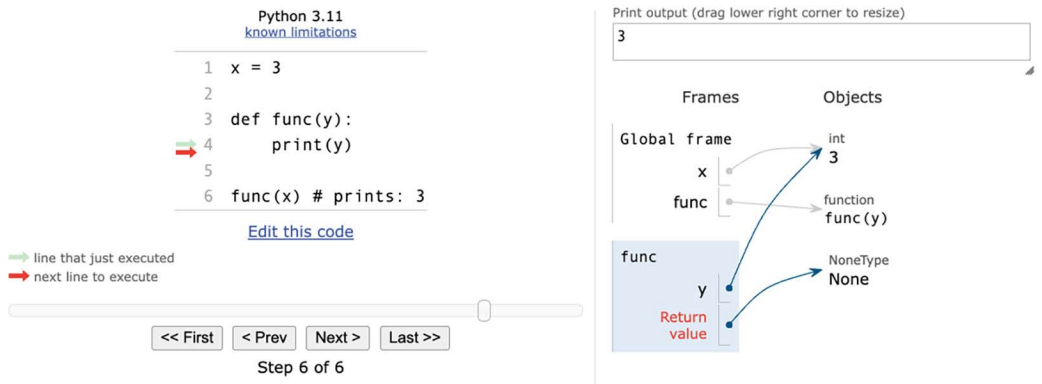

Figure 4.2: Understanding argument-passing with Python Tutor

The right-hand side of *Figure 4.2* depicts the state of the program when execution has reached the end, after `func()` has returned (`None`). Take a look at the **Frames** column, and note that we have two names, `x` and `func()`, in the global namespace (**Global frame**), pointing respectively to an **int** (with a value of `3`) and to a `function` object. Right beneath it, in the rectangle titled **func**, we can see the function's local namespace, in which only one name has been defined: `y`. Because we have called `func()` with `x` (line 6 on the left side of the figure), `y` is pointing to the same object that `x` is. This is what happens under the hood when an argument is passed to a function. If we had used the name `x` instead of `y` in the function definition, things would have been exactly the same (but perhaps a bit confusing at first)—there would be a local `x` in the function, and a global `x` outside, as we saw in the *Scopes and name resolution* section previously in this chapter.

So, in a nutshell, what really happens is that the function creates, in its local scope, the names defined as parameters and, when we call it, we tell Python which objects those names must be pointed toward.

Assignment to parameter names

Assignment to parameter names does not affect the caller. This is something that can be tricky to understand at first, so let us look at an example:

```
# key.points.assignment.py
x = 3

def func(x):
    x = 7  # defining a local x, not changing the global one

func(x)
print(x)  # prints: 3
```

In the preceding code, when we call the function with `func(x)`, the instruction `x = 7` is executed within the local scope of the `func()` function; the name `x` is pointed to an integer with a value of 7, leaving the global `x` unaltered.

Changing a mutable object

Changing a mutable object does affect the caller. This is important because although Python *appears to* behave differently with mutable objects, the behavior is, in fact, perfectly consistent. Let us look at an example:

```
# key.points.mutable.py
x = [1, 2, 3]

def func(x):
    x[1] = 42  # this affects the `x` argument!

func(x)
print(x)  # prints: [1, 42, 3]
```

As you can see, we changed the original object. If you think about it, there is nothing weird in this behavior. When we call `func(x)`, name `x` in the function's namespace is set to point to the same object as the global `x`. Within the body of the function, we are not changing the global `x`, in that we are not changing which object it points to. We are merely accessing the element at position 1 in that object and changing its value.

Remember *point 2* in the *Input parameters* section: *Assigning an object to a parameter name within a function does not affect the caller*. If that is clear to you, the following code should not be surprising:

```
# key.points.mutable.assignment.py
x = [1, 2, 3]

def func(x):
    x[1] = 42  # this changes the original `x` argument!
    x = "something else"  # this points x to a new string object

func(x)
print(x)  # still prints: [1, 42, 3]
```

Look at the two lines we have highlighted. At first, like before, we just access the caller object again, at position 1, and change that value to number `42`. Then, we reassign `x` to point to the `'something else'` string. This leaves the caller unaltered and, in fact, the output is the same as that of the previous snippet.

Take your time to play around with this concept, and experiment with prints and calls to the `id()` function until everything is clear in your mind. This is one of the key aspects of Python and it must be very clear, otherwise you risk introducing subtle bugs into your code. Once again, the Python Tutor website (`http://www.pythontutor.com/`) will help you a lot by giving you a visual representation of these concepts.

Now that we have a good understanding of input parameters and how they behave, let us look at the different ways of passing arguments to functions.

Passing arguments

There are four different ways of passing arguments to a function:

- Positional arguments
- Keyword arguments
- Iterable unpacking
- Dictionary unpacking

Let us look at them one by one.

Positional arguments

When we call a function, each positional argument is assigned to the parameter in the corresponding *position* in the function definition:

```
# arguments.positional.py
def func(a, b, c):
    print(a, b, c)

func(1, 2, 3)  # prints: 1 2 3
```

This is the most common way of passing arguments to functions (in some programming languages, this is the only way of passing arguments).

Keyword arguments

Keyword arguments in a function call are assigned to parameters using the `name=value` syntax:

```
# arguments.keyword.py
def func(a, b, c):
    print(a, b, c)

func(a=1, c=2, b=3)  # prints: 1 3 2
```

When we use keyword arguments, the order of the arguments does not need to match the order of the parameters in the function definition. This can make our code easier to read and debug. We do not need to remember (or look up) the order of parameters in a function definition. We can look at a function call and immediately know which argument corresponds to which parameter.

You can also use both positional and keyword arguments at the same time:

```
# arguments.positional.keyword.py
def func(a, b, c):
    print(a, b, c)

func(42, b=1, c=2)
```

Keep in mind, however, that **positional arguments always have to be listed before any keyword arguments**. For example, if you try something like this:

```
# arguments.positional.keyword.py
func(b=1, c=2, 42)  # positional arg after keyword args
```

You will get the following error:

```
$ python arguments.positional.keyword.py
  File "arguments.positional.keyword.py", line 7
    func(b=1, c=2, 42)  # positional arg after keyword args
                   ^
SyntaxError: positional argument follows keyword argument
```

Iterable unpacking

Iterable unpacking uses the syntax `*iterable_name` to pass the elements of an *iterable* as positional arguments to a function:

```
# arguments.unpack.iterable.py
def func(a, b, c):
    print(a, b, c)

values = (1, 3, -7)
func(*values)  # equivalent to: func(1, 3, -7)
```

This is a very useful feature, particularly when we need to programmatically generate arguments for a function.

Dictionary unpacking

Dictionary unpacking is to keyword arguments what iterable unpacking is to positional arguments. We use the syntax `**dictionary_name` to pass keyword arguments, constructed from the keys and values of a dictionary, to a function:

```
# arguments.unpack.dict.py
def func(a, b, c):
    print(a, b, c)

values = {"b": 1, "c": 2, "a": 42}
func(**values)  # equivalent to func(b=1, c=2, a=42)
```

Combining argument types

We have already seen that positional and keyword arguments can be used together, as long as they are passed in the proper order. We can also combine unpacking (of both kinds) with normal positional and keyword arguments. We can even combine unpacking multiple iterables and dictionaries.

Arguments must be passed in the following order:

- First, positional arguments: both ordinary (`name`) and iterable unpacking (`*name`)
- Next come keyword arguments (`name=value`), which can be mixed with iterable unpacking (`*name`)
- Finally, there is dictionary unpacking (`**name`), which can be mixed with keyword arguments (`name=value`)

This will be much easier to understand with an example:

```
# arguments.combined.py
def func(a, b, c, d, e, f):
    print(a, b, c, d, e, f)

func(1, *(2, 3), f=6, *(4, 5))
func(*(1, 2), e=5, *(3, 4), f=6)
func(1, **{"b": 2, "c": 3}, d=4, **{"e": 5, "f": 6})
func(c=3, *(1, 2), **{"d": 4}, e=5, **{"f": 6})
```

All the above calls to `func()` are equivalent and print `1 2 3 4 5 6`. Play around with this example until you are sure you understand it. Pay close attention to the errors you get when you get the order wrong.

The ability to unpack multiple iterables and dictionaries was introduced to Python by PEP 448. This PEP also introduced the ability to use unpacking in contexts other than just function calls. You can read all about it at `https://peps.python.org/pep-0448/`.

When combining positional and keyword arguments, it is important to remember that each parameter can only appear once in the argument list:

```
# arguments.multiple.value.py
def func(a, b, c):
    print(a, b, c)

func(2, 3, a=1)
```

Here, we are passing two values for parameter a: the positional argument 2 and the keyword argument a=1. This is illegal, so we get an error when we try to run it:

```
$ python arguments.multiple.value.py
Traceback (most recent call last):
  File "arguments.multiple.value.py", line 5, in <module>
    func(2, 3, a=1)
TypeError: func() got multiple values for argument 'a'
```

Defining parameters

Function parameters can be classified into five groups.

- Positional or keyword parameters: allow both positional and keyword arguments
- Variable positional parameters: collect an arbitrary number of positional arguments in a tuple
- Variable keyword parameters: collect an arbitrary number of keyword arguments in a dictionary
- Positional-only parameters: can only be passed as positional arguments
- Keyword-only parameters: can only be passed as keyword arguments

All the parameters in the examples we have seen so far in this chapter are regular positional or keyword parameters. We have seen how they can be passed as both positional and keyword arguments. There is not much more to say about them, so let us look at the other categories. Before we do, though, let us briefly look at optional parameters.

Optional parameters

Apart from the categories we have looked at here, parameters can also be classified as either *required* or *optional*. **Optional parameters** have a default value specified in the function definition. The syntax is `name=value`:

```
# parameters.default.py
def func(a, b=4, c=88):
    print(a, b, c)

func(1)  # prints: 1 4 88
func(b=5, a=7, c=9)  # prints: 7 5 9
func(42, c=9)  # prints: 42 4 9
func(42, 43, 44)  # prints: 42, 43, 44
```

Here, `a` is required, while `b` has the default value `4` and `c` has the default value `88`. It is important to note that, with the exception of keyword-only parameters, required parameters must always be to the left of all optional parameters in the function definition. Try removing the default value from `c` in the above example and see what happens.

Variable positional parameters

Sometimes you may prefer not to specify the exact number of positional parameters to a function; Python provides you with the ability to do this by using **variable positional parameters**. Let us look at a very common use case, the `minimum()` function. This is a function that calculates the minimum of its input values:

```
# parameters.variable.positional.py
def minimum(*n):
    # print(type(n))  # n is a tuple
    if n:  # explained after the code
        mn = n[0]
        for value in n[1:]:
            if value < mn:
                mn = value
        print(mn)

minimum(1, 3, -7, 9)  # n = (1, 3, -7, 9) - prints: -7
minimum()  # n = () - prints: nothing
```

As you can see, when we define a parameter with an asterisk, `*`, prepended to its name, we are telling Python that this parameter will collect a variable number of positional arguments when the function is called. Within the function, `n` is a tuple. Uncomment `print(type(n))` to see for yourself, and play around with it for a bit.

Note that a function can have at most one variable positional parameter—it would not make sense to have more. Python would have no way of deciding how to divide up the arguments between them. You also cannot specify a default value for a variable positional parameter. The default value is always an empty tuple.

Have you noticed how we checked whether `n` was not empty with a simple `if n:`? This is because collection objects evaluate to `True` when non-empty, and otherwise `False`, in Python. This is the case for tuples, sets, lists, dictionaries, and so on.

One other thing to note is that we may want to throw an error when we call the function with no parameters, instead of silently doing nothing. In this context, we are not concerned about making this function robust, but rather understanding variable positional parameters.

Did you notice that the syntax for defining variable positional parameters looks very much like the syntax for iterable unpacking? This is no coincidence. After all, the two features mirror each other. They are also frequently used together, since variable positional parameters save you from worrying about whether the length of the iterable you are unpacking matches the number of parameters in the function definition.

Variable keyword parameters

Variable keyword parameters are very similar to variable positional parameters. The only difference is the syntax (** instead of *) and the fact that they are collected in a dictionary:

```
# parameters.variable.keyword.py
def func(**kwargs):
    print(kwargs)

func(a=1, b=42)  # prints {'a': 1, 'b': 42}
func()  # prints {}
func(a=1, b=46, c=99)  # prints {'a': 1, 'b': 46, 'c': 99}
```

You can see that adding ** in front of the parameter name in the function definition tells Python to use that name to collect a variable number of keyword parameters. As in the case of variable positional parameters, each function can have at most one variable keyword parameter—and you cannot specify a default value.

Just like variable positional parameters resemble iterable unpacking, variable keyword parameters resemble dictionary unpacking. Dictionary unpacking is also often used to pass arguments to functions with variable keyword parameters.

The reason why being able to pass a variable number of keyword arguments is so important may not be evident at the moment, so how about a more realistic example? Let us define a function that connects to a database: we want to connect to a default database by simply calling this function with no parameters. We also want to connect to any other database by passing to the function the appropriate parameters. Before you read on, try to spend a couple of minutes figuring out a solution by yourself:

```
# parameters.variable.db.py
def connect(**options):
    conn_params = {
        "host": options.get("host", "127.0.0.1"),
        "port": options.get("port", 5432),
        "user": options.get("user", ""),
        "pwd": options.get("pwd", ""),
    }
    print(conn_params)
    # we then connect to the db (commented out)
    # db.connect(**conn_params)

connect()
connect(host="127.0.0.42", port=5433)
connect(port=5431, user="fab", pwd="gandalf")
```

Note that, in the function, we can prepare a dictionary of connection parameters (`conn_params`) using default values as fallbacks, allowing them to be overwritten if they are provided in the function call. There are better ways to do this with fewer lines of code, but we are not concerned with that right now. Running the preceding code yields the following result:

```
$ python parameters.variable.db.py
{'host': '127.0.0.1', 'port': 5432, 'user': '', 'pwd': ''}
{'host': '127.0.0.42', 'port': 5433, 'user': '', 'pwd': ''}
{'host': '127.0.0.1', 'port': 5431, 'user': 'fab', 'pwd': 'gandalf'}
```

Note the correspondence between the function calls and the output, and how default values are overridden according to what was passed to the function.

Positional-only parameters

Starting from Python 3.8, PEP 570 (`https://peps.python.org/pep-0570/`) introduced **positional-only parameters**. There is a new function parameter syntax, `/`, indicating that a set of the function parameters must be specified positionally and *cannot* be passed as keyword arguments. Let us see a simple example:

```
# parameters.positional.only.py
def func(a, b, /, c):
    print(a, b, c)

func(1, 2, 3)  # prints: 1 2 3
func(1, 2, c=3)  # prints 1 2 3
```

In the preceding example, we define a function, `func()`, which specifies three parameters: `a`, `b`, and `c`. The `/` in the function signature indicates that `a` and `b` must be passed positionally, that is, not by keyword.

The last two lines in the example show that we can call the function passing all three arguments positionally, or we can pass `c` by keyword. Both cases work fine, as `c` is defined after the `/` in the function signature. If we try to call the function by passing `a` or `b` by keyword, like so:

```
func(1, b=2, c=3)
```

This produces the following traceback:

```
Traceback (most recent call last):
  File "arguments.positional.only.py", line 7, in <module>
    func(1, b=2, c=3)
TypeError: func() got some positional-only arguments
passed as keyword arguments: 'b'
```

The preceding example shows us that Python is now complaining about how we called `func()`. We have passed `b` by keyword, but we are not allowed to do that.

Positional-only parameters can also be optional:

```
# parameters.positional.only.optional.py
def func(a, b=2, /):
    print(a, b)
```

```
func(4, 5)  # prints 4 5
func(3)  # prints 3 2
```

Let us see what this feature brings to the language with a few examples borrowed from the official documentation. One advantage is the ability to fully emulate behaviors of existing C-coded functions:

```
def divmod(a, b, /):
    "Emulate the built in divmod() function"
    return (a // b, a % b)
```

Another important use case is to preclude keyword arguments when the parameter name is not helpful:

```
len(obj='hello')
```

In the preceding example, the `obj` keyword argument impairs readability. Moreover, if we wish to refactor the internals of the `len` function, and rename `obj` to `the_object` (or any other name), the change is guaranteed not to break any client code, because there will not be any call to the `len()` function involving the now stale `obj` parameter name.

Finally, using positional-only parameters implies that whatever is on the left of / remains available for use in variable keyword arguments, as shown by the following example:

```
def func_name(name, /, **kwargs):
    print(name)
    print(kwargs)

func_name("Positional-only name", name="Name in **kwargs")
# Prints:
# Positional-only name
# {'name': 'Name in **kwargs'}
```

The ability to retain parameter names in function signatures for use in `**kwargs` can lead to simpler and cleaner code.

Let us now explore the mirror version of positional-only: keyword-only parameters.

Keyword-only parameters

Python 3 introduced **keyword-only parameters**. We are going to study them only briefly, as their use cases are not that frequent. There are two ways of specifying them, either after the variable positional parameters or after a bare *. Let us see an example of both:

```
# parameters.keyword.only.py
def kwo(*a, c):
    print(a, c)

kwo(1, 2, 3, c=7)  # prints: (1, 2, 3) 7
kwo(c=4)  # prints: () 4
# kwo(1, 2)  # breaks, invalid syntax, with the following error
# TypeError: kwo() missing 1 required keyword-only argument: 'c'

def kwo2(a, b=42, *, c):
    print(a, b, c)

kwo2(3, b=7, c=99)  # prints: 3 7 99
kwo2(3, c=13)  # prints: 3 42 13
# kwo2(3, 23)  # breaks, invalid syntax, with the following error
# TypeError: kwo2() missing 1 required keyword-only argument: 'c'
```

As anticipated, the function `kwo()` takes a variable number of positional parameters (`a`) and a keyword-only one, `c`. The results of the calls are straightforward and you can uncomment the third call to see what error Python returns.

The same applies to the function `kwo2()`, which differs from `kwo` in that it takes a positional argument, `a`, a keyword argument, `b`, and then a keyword-only one, `c`. You can uncomment the third call to see the error that is produced.

Now that you know how to specify different types of input parameters, let us see how you can combine them in function definitions.

Combining input parameters

You can combine different parameter types in the same function (in fact, it is often very useful to do so). As in the case of combining different types of arguments in the same function call, there are some restrictions on ordering:

- Positional-only parameters come first, followed by a `/`.

- Normal parameters go after any positional-only parameters.
- Variable positional parameters go after normal parameters.
- Keyword-only parameters go after variable positional parameters.
- Variable keyword parameters always go last.
- For positional-only and normal parameters, any required parameters must be defined before any optional parameters. This means that if you have an optional positional-only parameter, all your normal parameters must be optional too. This rule does not affect keyword-only parameters.

These rules can be a bit tricky to understand without an example, so let us look at a couple of them:

```
# parameters.all.py
def func(a, b, c=7, *args, **kwargs):
    print("a, b, c:", a, b, c)
    print("args:", args)
    print("kwargs:", kwargs)

func(1, 2, 3, 5, 7, 9, A="a", B="b")
```

Note the order of the parameters in the function definition. The execution of this yields the following:

```
$ python parameters.all.py
a, b, c: 1 2 3
args: (5, 7, 9)
kwargs: {'A': 'a', 'B': 'b'}
```

Let us now look at an example with keyword-only parameters:

```
# parameters.all.pkwonly.py
def allparams(a, /, b, c=42, *args, d=256, e, **kwargs):
    print("a, b, c:", a, b, c)
    print("d, e:", d, e)
    print("args:", args)
    print("kwargs:", kwargs)

allparams(1, 2, 3, 4, 5, 6, e=7, f=9, g=10)
```

Note that we have both positional-only and keyword-only parameters in the function declaration: `a` is positional-only, while `d` and `e` are keyword-only. They come after the `*args` variable positional argument, and it would be the same if they came right after a single `*` (in which case there would not be any variable positional parameter). The execution of this yields the following:

```
$ python parameters.all.pkwonly.py
a, b, c: 1 2 3
d, e: 256 7
args: (4, 5, 6)
kwargs: {'f': 9, 'g': 10}
```

One other thing to note is the names we gave to the variable positional and keyword parameters. You are free to choose differently but be aware that `args` and `kwargs` are the conventional names given to these parameters, at least generically.

More signature examples

To briefly recap on function signatures that use the positional- and keyword-only specifiers, here are some further examples. Omitting the variable positional and keyword parameters, for brevity, we are left with the following syntax:

```
def func_name(positional_only_parameters, /,
    positional_or_keyword_parameters, *,
    keyword_only_parameters):
```

First, we have positional-only, then positional or keyword parameters, and finally keyword-only ones.

Some other valid signatures are presented below:

```
def func_name(p1, p2, /, p_or_kw, *, kw):
def func_name(p1, p2=None, /, p_or_kw=None, *, kw):
def func_name(p1, p2=None, /, *, kw):
def func_name(p1, p2=None, /):
def func_name(p1, p2, /, p_or_kw):
def func_name(p1, p2, /):
```

All of the above are valid signatures, while the following would be invalid:

```
def func_name(p1, p2=None, /, p_or_kw, *, kw):
def func_name(p1=None, p2, /, p_or_kw=None, *, kw):
def func_name(p1=None, p2, /):
```

You can read about the grammar specifications in the official documentation:

`https://docs.python.org/3/reference/compound_stmts.html#function-definitions`

A useful exercise for you at this point would be to implement any of the above example signatures, print out the values of those parameters, like we have done in previous exercises, and play around passing arguments in different ways.

Avoid the trap! Mutable defaults

One thing to be aware of, in Python, is that default values are created at definition time; therefore, subsequent calls to the same function will possibly behave differently according to the mutability of their default values. Let us look at an example:

```
# parameters.defaults.mutable.py
def func(a=[], b={}):
    print(a)
    print(b)
    print("#" * 12)
    a.append(len(a))  # this will affect a's default value
    b[len(a)] = len(a)  # and this will affect b's one

func()
func()
func()
```

Both parameters have mutable default values. This means that, if you affect those objects, any modification will stick around in subsequent function calls. See if you can understand the output of those calls:

```
$ python parameters.defaults.mutable.py
[]
{}
############
[0]
{1: 1}
############
[0, 1]
{1: 1, 2: 2}
############
```

While this behavior may seem weird at first, it actually makes sense, and it is very handy—when using **memoization** techniques, for example. Even more interesting is what happens when, between the calls, we introduce one that does not use defaults, such as this:

```
# parameters.defaults.mutable.intermediate.call.py
func()
func(a=[1, 2, 3], b={"B": 1})
func()
```

When we run this code, this is the output:

```
$ python parameters.defaults.mutable.intermediate.call.py
[]
{}
############
[1, 2, 3]
{'B': 1}
############
[0]
{1: 1}
############
```

This output shows us that the defaults are retained even if we call the function with other values. One question that comes to mind is, how do I get a fresh empty value every time? Well, the convention is the following:

```
# parameters.defaults.mutable.no.trap.py
def func(a=None):
    if a is None:
        a = []
    # do whatever you want with `a` ...
```

Note that, by using the preceding technique, if `a` is not passed when calling the function, we always get a brand new, empty list.

After a thorough exposition of input parameters, it is now time to look at the other side of the coin, returning output values.

Return values

We have already said that to return something from a function we need to use the `return` statement, followed by what we want to return. There can be as many `return` statements as needed in the body of a function.

On the other hand, if within the body of a function we do not return anything, or we invoke a bare `return` statement, the function will return `None`. This behavior is harmless when it is not needed, but allows for interesting patterns, and confirms Python as a very consistent language.

We say it is harmless because you are never forced to collect the result of a function call. We will show you what we mean with an example:

```
# return.none.py
def func():
    pass

func()  # the return of this call won't be collected. It's lost.
a = func()  # the return of this one instead is collected into `a`
print(a)  # prints: None
```

Note that the whole body of the function is composed only of the `pass` statement. As the official documentation tells us, `pass` is a null operation, as, when it is executed, nothing happens. It is useful as a placeholder when a statement is required syntactically but no code needs to be executed. In other languages, we would probably just indicate that with a pair of curly brackets ({}), which define an *empty scope*; but in Python, a scope is defined by indenting code, therefore a statement such as `pass` is necessary.

Notice also that the first call to `func()` returns a value (`None`) that we do not collect. As we mentioned before, collecting the return value of a function call is not mandatory.

Let us see a more interesting example. Remember that, in *Chapter 1, A Gentle Introduction to Python*, we talked about the *factorial* function. Let us write our own implementation here (for simplicity, we will assume the function is always called correctly with appropriate values, so we do not need to sanity-check the input argument):

```
# return.single.value.py
def factorial(n):
    if n in (0, 1):
        return 1
```

```
    result = n
    for k in range(2, n):
        result *= k
    return result


f5 = factorial(5)  # f5 = 120
```

Note that we have two points of return. If `n` is either `0` or `1`, we return `1`. Otherwise, we perform the required calculation and return `result`.

In Python, it is common to use the `in` operator to do a membership check, as we did in the preceding example, instead of the more verbose:

```
if n == 0 or n == 1:
    ...
```

Let us now try to write this function a little bit more succinctly:

```
# return.single.value.2.py
from functools import reduce
from operator import mul

def factorial(n):
    return reduce(mul, range(1, n + 1), 1)

f5 = factorial(5)  # f5 = 120
```

This simple example shows how Python is both elegant and concise. This implementation is readable even if we have never seen `reduce()` or `mul()`. If you cannot read or understand it, set aside a few minutes, and do some research in the Python documentation until its behavior is clear to you. Being able to look up functions in the documentation and understand code written by someone else is a task that every developer needs to be able to perform.

To this end, make sure you look up the `help()` function, which proves quite helpful when exploring with the console.

Returning multiple values

To return multiple values is easy: you just use tuples. Let us look at a simple example that mimics the `divmod()` built-in function:

```
# return.multiple.py
def moddiv(a, b):
    return a // b, a % b

print(moddiv(20, 7))  # prints (2, 6)
```

We could have wrapped the part that is highlighted in the preceding code within brackets, but there is no need for that. The preceding function returns both the result and the remainder of the division, at the same time.

In the source code for this example, we have left a simple example of a test function to make sure the code is doing the correct calculation.

A few useful tips

When writing functions, it is very useful to follow guidelines so that you write them well. We will quickly point some of them out:

- **Functions should do one thing**: Functions that do one thing are easy to describe in one short sentence; functions that do multiple things can be split into smaller functions that do one thing. These smaller functions are usually easier to read and understand.
- **Functions should be small**: The smaller they are, the easier it is to test and write them so that they do one thing.
- **The fewer input parameters, the better**: Functions that take a lot of parameters quickly become hard to manage (among other issues).
- **Functions should be consistent in their return values**: Returning `False` and returning `None` are not the same thing, even if, within a Boolean context, they both evaluate to `False`. `False` means that we have information (`False`), while `None` means that there is no information. Try writing functions that return in a consistent way, no matter what happens in their logic.
- **Functions should have no side effects**: In functional programming, there is the concept of **pure functions**. This type of function adheres to two main principles:

- **Deterministic output**: This means that given the same set of inputs, the output produced will always be the same. In other words, the function's behavior is not dependent on any external or global state that might change during execution.
- **No side effects**: This means that pure functions do not cause any observable side effects in the system. That is, they do not alter any external state, like modifying global variables or performing I/O operations like reading from or writing to a file or the display.

While you should aim to write pure functions whenever possible, it is important that those you write should at least have no side effects. They should not affect the value of the arguments they are called with.

This is probably the hardest statement to understand at this point, so we will give you an example using lists. In the following code, note how `numbers` is not sorted by the `sorted()` function, which returns a sorted copy of `numbers`. Conversely, the `list.sort()` method is acting on the `numbers` object itself, and that is fine because it is a method (a function that belongs to an object and therefore has the right to modify it):

```
>>> numbers = [4, 1, 7, 5]
>>> sorted(numbers)  # won't sort the original `numbers` list
[1, 4, 5, 7]
>>> numbers  # let's verify
[4, 1, 7, 5]  # good, untouched
>>> numbers.sort()  # this will act on the list
>>> numbers
[1, 4, 5, 7]
```

Follow these guidelines and you will automatically shield yourself from certain types of bugs.

Chapter 3 of *Clean Code*, by Robert C. Martin, is dedicated to functions, and it is one of the best sets of guidelines we have ever read on the subject.

Recursive functions

When a function calls itself to produce a result, it is said to be **recursive**. Sometimes recursive functions are very useful, in that they make it easier to write the logic. Some algorithms are very easy to write using recursion, while others are not. There is no recursive function that cannot be rewritten in an iterative fashion, so it is usually up to the programmer to choose the best approach for the case at hand.

The body of a recursive function usually has two sections: one where the return value depends on a subsequent call to itself, and one where it does not (called the **base case**).

As an example, we can consider the (hopefully now familiar) **factorial** function, *N!*. The base case is when *N* is either 0 or 1—the function returns 1 with no need for further calculation. On the other hand, in the general case, *N!* returns the product:

```
1 * 2 * ... * (N-1) * N
```

If you think about it, *N!* can be rewritten like this: *N! = (N-1)! * N*. As a practical example, consider this:

```
5! = 1 * 2 * 3 * 4 * 5 = (1 * 2 * 3 * 4) * 5 = 4! * 5
```

Let us write this down in code:

```
# recursive.factorial.py
def factorial(n):
    if n in (0, 1):  # base case
        return 1
    return factorial(n - 1) * n  # recursive case
```

Recursive functions are often used when writing algorithms, and they can be really fun to write. As an exercise, try to solve a couple of simple problems using both a recursive and an iterative approach. Good candidates for practice might be calculating Fibonacci numbers or the length of a string—things like that.

When writing recursive functions, always consider how many nested calls you make, since there is a limit. For further information on this, check out `sys.getrecursionlimit()` and `sys.setrecursionlimit()`.

Anonymous functions

One last type of function that we want to talk about is **anonymous** functions. These functions, which are called **lambdas** in Python, are usually used when a fully-fledged function with its own name would be overkill, and all we want is a quick, simple one-liner.

Imagine that we wanted a list of all the numbers up to a certain value of *N* that are also multiples of five. We could use the `filter()` function for this, which will require a function and an iterable as input. The return value is a filter object that, when iterated over, yields the elements from the input iterable for which the function returns `True`. Without using an anonymous function, we might do something like this:

```
# filter.regular.py
def is_multiple_of_five(n):
    return not n % 5

def get_multiples_of_five(n):
    return list(filter(is_multiple_of_five, range(n)))
```

Note how we use `is_multiple_of_five()` to filter through the first *n* natural numbers. This seems a bit excessive—the task is simple and we do not need to keep the `is_multiple_of_five()` function around for anything else. Let us rewrite it using a lambda function:

```
# filter.lambda.py
def get_multiples_of_five(n):
    return list(filter(lambda k: not k % 5, range(n)))
```

The logic is the same, but the filtering function is now a lambda. Defining a lambda is very easy and follows this form:

```
func_name = lambda [parameter_list]: expression
```

A function object is returned, which is equivalent to this:

```
def func_name([parameter_list]):
    return expression
```

Note that optional parameters are indicated following the common syntax of wrapping them in square brackets.

Let us look at another couple of examples of equivalent functions, defined in both forms:

```
# lambda.explained.py
# example 1: adder
def adder(a, b):
    return a + b
```

```
# is equivalent to:
adder_lambda = lambda a, b: a + b

# example 2: to uppercase
def to_upper(s):
    return s.upper()

# is equivalent to:
to_upper_lambda = lambda s: s.upper()
```

The preceding examples are very simple. The first one adds two numbers, and the second one produces the uppercase version of a string. Note that we assigned what is returned by the `lambda` expressions to a name (`adder_lambda`, `to_upper_lambda`), but there is no need for that when you use lambdas in the way we did in the `filter()` example.

Function attributes

Every function is a fully fledged object and, as such, it has several attributes. Some of them are special and can be used in an introspective way to inspect the function object at runtime. The following script is an example that shows a few of them and how to display their value for an example function:

```
# func.attributes.py
def multiplication(a, b=1):
    """Return a multiplied by b."""
    return a * b

if __name__ == "__main__":
    special_attributes = [
        "__doc__",
        "__name__",
        "__qualname__",
        "__module__",
        "__defaults__",
        "__code__",
        "__globals__",
        "__dict__",
        "__closure__",
```

```
        "__annotations__",
        "__kwdefaults__",
    ]

    for attribute in special_attributes:
        print(attribute, "->", getattr(multiplication, attribute))
```

We used the built-in `getattr()` function to get the value of those attributes. `getattr(obj, attribute)` is equivalent to `obj.attribute` and comes in handy when we need to dynamically get an attribute at runtime, taking the name of the attribute from a variable (as in this example). Running this script yields:

```
$ python func.attributes.py
__doc__ -> Return a multiplied by b.
__name__ -> multiplication
__qualname__ -> multiplication
__module__ -> __main__
__defaults__ -> (1,)
__code__ -> <code object multiplication at 0x102ce1550,
            file "func.attributes.py", line 2>
__globals__ -> {... omitted ...}
__dict__ -> {}
__closure__ -> None
__annotations__ -> {}
__kwdefaults__ -> None
```

We have omitted the value of the `__globals__` attribute, as it was too big. An explanation of the meaning of this attribute can be found in the *Callable types* section of the *Python Data Model* documentation page:

`https://docs.python.org/3/reference/datamodel.html#the-standard-type-hierarchy`

You can use the built-in `dir()` function to get a list of all the attributes of any object.

One thing to notice in the previous example is the use of this clause:

```
if __name__ == "__main__":
```

This line makes sure that whatever follows is only executed when the module is run directly. When you run a Python script, Python sets the `__name__` variable to `"__main__"` in that script. Conversely, when you import a Python script as a module into another script, the `__name__` variable is set to the name of the script/module being imported.

Built-in functions

Python comes with a lot of built-in functions. They are available anywhere, and you can get a list of them by inspecting the `builtins` module with `dir(__builtins__)`, or by going to the official Python documentation. Unfortunately, we do not have the room to go through all of them here. We have already seen some of them, such as `any`, `bin`, `bool`, `divmod`, `filter`, `float`, `getattr`, `id`, `int`, `len`, `list`, `min`, `print`, `set`, `tuple`, `type`, and `zip`, but there are many more, which you should read about at least once. Get familiar with them, experiment, write a small piece of code for each of them, and make sure you have them at your fingertips so that you can use them when needed.

You can find a list of built-in functions in the official documentation, here: `https://docs.python.org/3/library/functions.html`.

Documenting your code

We are big fans of code that does not need documentation. When we write elegant code, following established principles, the code should come out as self-explanatory, with documentation being almost unnecessary. Nevertheless, adding a docstring to a function, or a comment with important information, can be very useful.

You can find the guidelines for documenting Python in PEP 257 – Docstring conventions at `https://peps.python.org/pep-0257/`, but we will show you the basics here.

Python is documented with strings, which are aptly called **docstrings**. Any object can be documented, and we can use either one-line or multi-line docstrings. One-liners are very simple. They should not provide another signature for the function, but instead state its purpose:

```
# docstrings.py
def square(n):
    """Return the square of a number n."""
    return n**2

def get_username(userid):
    """Return the username of a user given their id."""
    return db.get(user_id=userid).username
```

Using triple double-quoted strings allows you to expand easily later. Use sentences that end in a period, and do not leave blank lines before or after.

Multiline comments are structured in a similar way. There should be a one-liner that briefly gives you the gist of what the object is about, and then a more verbose description. As an example, we have documented a fictitious `connect()` function, using the **Sphinx** notation, in the following example:

```
def connect(host, port, user, password):
    """Connect to a database.

    Connect to a PostgreSQL database directly, using the given
    parameters.

    :param host: The host IP.
    :param port: The desired port.
    :param user: The connection username.
    :param password: The connection password.
    :return: The connection object.
    """
    # body of the function here...
    return connection
```

Sphinx is one of the most widely used tools for creating Python documentation—in fact, the official Python documentation was written with it. It is definitely worth spending some time checking it out.

The `help()` built-in function, which is intended for interactive use, creates a documentation page for an object using its docstring.

Importing objects

Now that we know a lot about functions, let us look at how to use them. The whole point of writing functions is to be able to reuse them later and, in Python, this translates to importing them into the namespace where they are needed. There are many ways to import objects into a namespace, but the most common ones are `import module_name` and `from module_name import function_name`. Of course, these are quite simplistic examples, but bear with us for the time being.

The `import module_name` form finds the `module_name` module and defines a name for it in the local namespace, where the `import` statement is executed. The `from module_name import identifier` form is a little bit more complicated than that but basically does the same thing. It finds `module_name` and searches for an attribute (or a submodule) and stores a reference to `identifier` in the local namespace. Both forms have the option to change the name of the imported object using the `as` clause:

```
from mymodule import myfunc as better_named_func
```

Just to give you a flavor of what importing looks like, here is an example from a test module of one of Fabrizio's projects (notice that the blank lines between blocks of imports follow the guidelines from PEP 8 at `https://peps.python.org/pep-0008/#imports`: standard library first, then third party, and finally local code):

```
# imports.py
from datetime import datetime, timezone  # two imports, same line
from unittest.mock import patch  # single import

import pytest  # third party library

from core.models import (  # multiline import
    Exam,
    Exercise,
    Solution,
)
```

When we have a structure of files starting in the root of our project, we can use the dot notation to get to the object we want to import into our current namespace, be it a package, a module, a class, a function, or anything else.

The `from module import` syntax also allows a catch-all clause, `from module import *`, which is sometimes used to get all the names from a module into the current namespace at once. This practice is frowned upon for several reasons, relating to performance and the risk of silently shadowing other names. You can read all that there is to know about imports in the official Python documentation but, before we leave the subject, let us give you a better example.

Imagine that we have defined a couple of functions, `square(n)` and `cube(n)`, in a module, `funcdef.py`, which is in the `util` folder. We want to use them in a couple of modules that are at the same level as the `util` folder, called `func_import.py` and `func_from.py`. Showing the tree structure of that project produces something like this:

```
├── func_from.py
├── func_import.py
├── util
│   ├── __init__.py
│   └── funcdef.py
```

Before we show you the code of each module, please remember that in order to tell Python that it is actually a package, we need to put an `__init__.py` module in it.

There are two things to note about the `__init__.py` file. First, it is a fully fledged Python module so you can put code into it as you would with any other module. Second, as of Python 3.3, its presence is no longer required to make a folder be interpreted as a Python package.

The code is as follows:

```
# util/funcdef.py
def square(n):
    return n**2

def cube(n):
    return n**3

# func_import.py
import util.funcdef

print(util.funcdef.square(10))
print(util.funcdef.cube(10))

# func_from.py
from util.funcdef import square, cube

print(square(10))
print(cube(10))
```

Both these files, when executed, print `100` and `1000`. You can see how differently we then access the `square` and `cube` functions, according to how and what we imported in the current scope.

Relative imports

The type of import we have seen so far is called an **absolute import**; that is, it defines the whole path of either the module that we want to import or from which we want to import an object. There is another way of importing objects into Python, which is called a **relative import**. Relative imports are done by adding as many leading dots in front of the module as the number of folders we need to backtrack, to find what we are searching for. Simply put, it is something such as this:

```
from .mymodule import myfunc
```

Relative imports are quite useful when restructuring projects. Not having the full path in the imports allows the developer to move things around without having to rename too many of those paths.

For a complete explanation of relative imports, refer to PEP 328: `https://peps.python.org/pep-0328/`.

In later chapters, we will create projects using different libraries and use several different types of imports, including relative ones, so make sure you take a bit of time to read up about them in the official Python documentation.

One final example

Before we finish off this chapter, let us go through one last example. We could write a function to generate a list of prime numbers up to a limit; we have already seen the code for this in *Chapter 3*, *Conditionals and Iteration*, so let us make it a function and, to keep it interesting, let us optimize it a bit.

First of all, we do not need to divide by all the numbers from *2* to *N-1* to decide whether a number, *N*, is prime. We can stop at $\sqrt{N}$ (the square root of *N*). Moreover, we do not need to test the division for all the numbers from *2* to $\sqrt{N}$, as we can just use the primes in that range. We leave it up to you to figure out the math for why this works, if you are interested.

Let us see how the code changes:

```
# primes.py
from math import sqrt, ceil

def get_primes(n):
```

```
    """Calculate a list of primes up to n (included)."""
    primelist = []
    for candidate in range(2, n + 1):
        is_prime = True
        root = ceil(sqrt(candidate))  # division limit
        for prime in primelist:  # we try only the primes
            if prime > root:  # no need to check any further
                break
            if candidate % prime == 0:
                is_prime = False
                break
        if is_prime:
            primelist.append(candidate)
    return primelist
```

The code is the same as that in the previous chapter. We have changed the division algorithm so that we only test divisibility using the previously calculated primes, and we stopped once the testing divisor was greater than the root of the candidate. We used the `primelist` result list to get the primes for the division and calculated the root value using a fancy formula, the integer value of the ceiling of the root of the candidate. While a simple `int(k ** 0.5) + 1` would have also served our purpose, the formula we chose is cleaner and requires a couple of imports, which is what we wanted to show. Check out the functions in the `math` module—they are very interesting!

Summary

In this chapter, we explored the world of functions. They are very important and, from now on, we will use them in virtually everything we do. We talked about the main reasons for using them, the most important of which are code reuse and implementation hiding.

We saw that a function object is like a box that takes optional inputs and may produce outputs. We can feed input arguments to a function in many different ways, using positional and keyword arguments, and using variable syntax for both types.

You should now know how to write a function, document it, import it into your code, and call it.

In the next chapter, we will be picking up the pace a little bit, so we suggest you spend a bit of time consolidating and enriching the knowledge you have gathered so far by experimenting with code and reading the Python official documentation.

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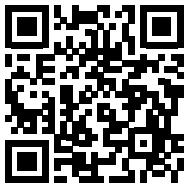

5

Comprehensions and Generators

> *"It's not the daily increase but daily decrease. Hack away at the unessential."*
>
> *—Bruce Lee*

The second part of the above quote, "hack away at the unessential," is to us what makes a computer program elegant. We constantly strive to find better ways of doing things so that we do not waste time or memory.

There are valid reasons for not pushing our code up to the maximum limit. For example, sometimes we have to sacrifice readability or maintainability to achieve a negligible improvement. It does not make sense to have a web page served in 1 second with unreadable, complicated code when we could serve it in 1.05 seconds with readable, clean code.

On the other hand, sometimes it is perfectly reasonable to try to shave off a millisecond from a function, especially when the function is meant to be called thousands of times. One millisecond saved over thousands of calls adds up to seconds saved overall, which might be meaningful for your application.

In light of these considerations, the focus of this chapter will not be to give you the tools to push your code to the absolute limits of performance and optimization *no matter what*, but rather to enable you to write efficient, elegant code that reads well, runs fast, and does not waste resources in an obvious way.

In this chapter, we are going to cover the following:

- The `map()`, `zip()`, and `filter()` functions
- Comprehensions
- Generators
- Performance

We will perform several measurements and comparisons and cautiously draw some conclusions. Please do keep in mind that on a different machine with a different setup or operating system, results may vary.

Take a look at this code:

```
# squares.py
def square1(n):
    return n**2  # squaring through the power operator

def square2(n):
    return n * n  # squaring through multiplication
```

Both functions return the square of `n`, but which is faster? From a simple benchmark that we ran, it looks like the second is slightly faster. If you think about it, it makes sense: calculating the power of a number involves multiplication. Therefore, whatever algorithm you may use to perform the power operation, it is not likely to beat a simple multiplication such as the one in `square2`.

Do we care about this result? In most cases, no. If you are coding an e-commerce website, chances are you will never need to raise a number to the second power, and if you do, it is likely to be a sporadic operation. You do not need to concern yourself with saving a fraction of a microsecond on a function you call a few times.

So, when does optimization become important? One common case is when you have to deal with huge collections of data. If you are applying the same function on a million `customer` objects, then you want your function to be tuned up to its best. Gaining one-tenth of a second on a function called one million times saves you 100,000 seconds, which is about 27.7 hours. So, let us focus on collections, and see which tools Python gives you to handle them with efficiency and grace.

Many of the concepts we will see in this chapter are based on iterators and iterables, which we encountered in *Chapter 3*, *Conditionals and Iteration*. We will see how to code a custom iterator and iterable objects in *Chapter 6*, *OOP, Decorators, and Iterators*.

Some of the objects we are going to explore in this chapter are iterators, which save memory by only operating on a single element of a collection at a time rather than creating a modified copy. As a result, some extra work is needed if we just want to show the result of the operation. We will often resort to wrapping the iterator in a `list()` constructor. This is because passing an iterator to `list()` exhausts it and puts all the generated items in a newly created list, which we can easily print to show you its content. Let us see an example of using the technique on a `range` object:

```
# list.iterable.txt
>>> range(7)
range(0, 7)
>>> list(range(7))  # put all elements in a list to view them
[0, 1, 2, 3, 4, 5, 6]
```

We have highlighted the result of typing `range(7)` into a Python console. Notice that it does not show the contents of the `range` because `range` never actually loads the entire sequence of numbers into memory. The second highlighted line shows how wrapping the `range` in a `list()` allows us to see the numbers it generates.

Let us start looking at the various tools that Python provides for efficiently operating on collections of data.

The map, zip, and filter functions

We will start by reviewing `map()`, `filter()`, and `zip()`, which are the main built-in functions you can employ when handling collections, and then we will learn how to achieve the same results using two important constructs: **comprehensions** and **generators**.

map

According to the official Python documentation (`https://docs.python.org/3/library/functions.html#map`), the following is true:

> *map(function, iterable, *iterables)*
>
> *Return an iterator that applies function to every item of iterable, yielding the results. If additional iterables arguments are passed, function must take that many arguments and is applied to the items from all iterables in parallel. With multiple iterables, the iterator stops when the shortest iterable is exhausted.*

We will explain the concept of yielding later in the chapter. For now, let us translate this into code—we will use a `lambda` function that takes a variable number of positional arguments, and returns them as a tuple:

```
# map.example.txt
>>> map(lambda *a: a, range(3))  # 1 iterable
<map object at 0x7f0db97adae0>  # Not useful! Let us use list
>>> list(map(lambda *a: a, range(3)))  # 1 iterable
[(0,), (1,), (2,)]
>>> list(map(lambda *a: a, range(3), "abc"))  # 2 iterables
[(0, 'a'), (1, 'b'), (2, 'c')]
>>> list(map(lambda *a: a, range(3), "abc", range(4, 7)))  # 3
[(0, 'a', 4), (1, 'b', 5), (2, 'c', 6)]
>>> # map stops at the shortest iterator
>>> list(map(lambda *a: a, (), "abc"))  # empty tuple is shortest
[]
>>> list(map(lambda *a: a, (1, 2), "abc"))  # (1, 2) shortest
[(1, 'a'), (2, 'b')]
>>> list(map(lambda *a: a, (1, 2, 3, 4), "abc"))  # "abc" shortest
[(1, 'a'), (2, 'b'), (3, 'c')]
```

In the preceding code, you can see why we have to wrap calls in `list()`. Without it, we get the string representation of a `map` object. Python's default string representation for objects gives their type and memory location which, in this context, is not particularly useful to us.

You can also notice how the elements of each iterable are applied to the function; at first, the first element of each iterable is applied, then the second one of each iterable, and so on. Notice also that `map()` stops when the shortest of the iterables we called it with is exhausted. This is a very useful behavior; it does not force us to level off all the iterables to a common length, nor does it break if they are not all the same length.

As a more interesting example, suppose we have a collection of student dictionaries, each of which contains a nested dictionary of the student's credits. We want to sort the students based on the sum of their credits. However, the data as it is does not allow for a straightforward application of the sorting function.

To solve the problem, we are going to apply the **decorate-sort-undecorate** idiom (also known as **Schwartzian transform**). It is a technique that was quite popular in older Python versions, when sorting did not support the use of *key functions*. Nowadays, it is not needed as often, but it still occasionally comes in handy.

To **decorate** an object means to transform it, either adding extra data to it or putting it into another object. Conversely, to **undecorate** an object means to revert the decorated object to its original form.

This technique has nothing to do with Python decorators, which we will explore later in the book.

In the following example, we can see how `map()` is used to apply this idiom:

```
# decorate.sort.undecorate.py
from pprint import pprint

students = [
    dict(id=0, credits=dict(math=9, physics=6, history=7)),
    dict(id=1, credits=dict(math=6, physics=7, latin=10)),
    dict(id=2, credits=dict(history=8, physics=9, chemistry=10)),
    dict(id=3, credits=dict(math=5, physics=5, geography=7)),
]

def decorate(student):
    # create a 2-tuple (sum of credits, student) from student dict
    return (sum(student["credits"].values()), student)

def undecorate(decorated_student):
    # discard sum of credits, return original student dict
    return decorated_student[1]

print(students[0])
print(decorate(students[0])

students = sorted(map(decorate, students), reverse=True)
students = list(map(undecorate, students))
pprint(students)
```

Let us start by understanding what each student object is. In fact, let us print the first one:

```
{'id': 0, 'credits': {'math': 9, 'physics': 6, 'history': 7}}
```

You can see that it is a dictionary with two keys: `id` and `credits`. The value of `credits` is also a dictionary in which there are three subject/grade key/value pairs. As you may recall from *Chapter 2*, *Built-in Data Types*, calling `dict.values()` returns an iterable object, with only the dictionary's values. Therefore, `sum(student["credits"].values())` for the first student is equivalent to `sum((9, 6, 7))`.

Let us print the result of calling `decorate` with the first student:

```
(22, {'id': 0, 'credits': {'math': 9, 'physics': 6, 'history': 7}})
```

If we decorate all the students like this, we can sort them on their total number of credits by just sorting the list of tuples. To apply the decoration to each item in `students`, we call `map(decorate, students)`. We sort the result, and then we undecorate in a similar fashion.

Printing `students` after running the whole code yields the following:

```
[{'credits': {'chemistry': 10, 'history': 8, 'physics': 9}, 'id': 2},
 {'credits': {'latin': 10, 'math': 6, 'physics': 7}, 'id': 1},
 {'credits': {'history': 7, 'math': 9, 'physics': 6}, 'id': 0},
 {'credits': {'geography': 7, 'math': 5, 'physics': 5}, 'id': 3}]
```

As you can see, the student objects have indeed been sorted by the sums of their credits.

For more on the *decorate-sort-undecorate* idiom, there is a good introduction in the *Sorting HOW TO* section of the official Python documentation:

`https://docs.python.org/3.12/howto/sorting.html#decorate-sort-undecorate`

One thing to notice about the sorting part is what happens when two or more students share the same total sum. The sorting algorithm would then proceed to sort the tuples by comparing the `student` objects with each other. This does not make any sense and, in more complex cases, could lead to unpredictable results, or even errors. If you want to avoid this issue, one simple solution is to create a three-tuple instead of a two-tuple, having the sum of credits in the first position, the position of the `student` object in the original `students` list in second place, and the `student` object itself in third place. This way, if the sum of credits is the same, the tuples will be sorted against the position, which will always be different, and therefore enough to resolve the sorting between any pair of tuples.

zip

We have already covered `zip()` in the previous chapters, so let us just define it properly, after which we want to show you how you could combine it with `map()`.

According to the Python documentation (`https://docs.python.org/3/library/functions.html#zip`), the following applies:

> *zip(*iterables, strict=False)*
>
> *... returns an iterator of tuples, where the i-th tuple contains the i-th element from each of the argument iterables.*
>
> *Another way to think of zip() is that it turns rows into columns, and columns into rows. This is similar to transposing a matrix.*

Let us see an example:

```
# zip.grades.txt
>>> grades = [18, 23, 30, 27]
>>> avgs = [22, 21, 29, 24]
>>> list(zip(avgs, grades))
[(22, 18), (21, 23), (29, 30), (24, 27)]
>>> list(map(lambda *a: a, avgs, grades))  # equivalent to zip
[(22, 18), (21, 23), (29, 30), (24, 27)]
```

Here, we are zipping together the average and the grade for the last exam for each student. Notice how easy it is to reproduce `zip()` using `map()` (the last two instructions of the example). Once again, we have to use `list()` to visualize the results.

Like `map()`, `zip()` will normally stop as soon as it reaches the end of the shortest iterable. This can, however, mask problems with the input data, leading to bugs. For example, suppose we need to combine a list of students' names and a list of grades into a dictionary mapping each student's name to their grade. A mistake in data entry could result in the list of grades being shorter than the list of students. Here is an example:

```
# zip.strict.txt
>>> students = ["Sophie", "Alex", "Charlie", "Alice"]
>>> grades = ["A", "C", "B"]
```

```
>>> dict(zip(students, grades))
{'Sophie': 'A', 'Alex': 'C', 'Charlie': 'B'}
```

Notice that there is no entry for `"Alice"` in the dictionary. The default behavior of `zip()` has masked the data error. For this reason, the `strict` keyword-only parameter was added in Python 3.10. If `zip()` receives `strict=True` as an argument, it raises an exception if the iterables do not all have the same length:

```
>>> dict(zip(students, grades, strict=True))
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
ValueError: zip() argument 2 is shorter than argument 1
```

The `itertools` module also provides a `zip_longest()` function. It behaves like `zip()` but stops only when the longest iterable is exhausted. Shorter iterables are padded with a value that can be specified as an argument, which defaults to `None`.

filter

According to the Python documentation (`https://docs.python.org/3/library/functions.html#filter`), the following applies:

> *filter(function, iterable)*
>
> *Construct an iterator from those elements of iterable for which function is true. iterable may be either a sequence, a container which supports iteration, or an iterator. If function is None, the identity function is assumed, that is, all elements of iterable that are false are removed.*

Let us see a quick example:

```
# filter.txt
>>> test = [2, 5, 8, 0, 0, 1, 0]
>>> list(filter(None, test))
[2, 5, 8, 1]
>>> list(filter(lambda x: x, test))  # equivalent to previous one
[2, 5, 8, 1]
```

```
>>> list(filter(lambda x: x > 4, test))  # keep only items > 4
[5, 8]
```

Notice how the second call to `filter()` is equivalent to the first one. If we pass a function that takes one argument and returns the argument itself, only those arguments that are `True` will make the function return `True`. This behavior is the same as passing `None`. It is often a good exercise to mimic some of the built-in Python behaviors. When you succeed, you can say you fully understand how Python behaves in a specific situation.

Armed with `map()`, `zip()`, and `filter()` (and several other functions from the Python standard library), we can manipulate sequences very effectively. But these functions are not the only way to do it. Let us look at one of the most powerful features of Python: *comprehensions*.

Comprehensions

A comprehension is a concise notation for performing some operation on each element of a collection of objects, and/or selecting a subset of elements that satisfy some condition. They are borrowed from the functional programming language Haskell (`https://www.haskell.org/`) and, together with iterators and generators, contribute to giving Python a functional flavor.

Python offers several types of comprehensions: list, dictionary, and set. We will concentrate on list comprehensions; once you understand them, the other types will be easy to grasp.

Let us start with a simple example. We want to calculate a list with the squares of the first 10 natural numbers. We could use a `for` loop and append a square to the list in each iteration:

```
# squares.for.txt
>>> squares = []
>>> for n in range(10):
...     squares.append(n**2)
...
>>> squares
[0, 1, 4, 9, 16, 25, 36, 49, 64, 81]
```

This is not very elegant as we have to initialize the list first. With `map()`, we can achieve the same thing in just one line of code:

```
# squares.map.txt
>>> squares = list(map(lambda n: n**2, range(10)))
>>> squares
[0, 1, 4, 9, 16, 25, 36, 49, 64, 81]
```

Now, let us see how to achieve the same result using a list comprehension:

```
# squares.comprehension.txt
>>> [n**2 for n in range(10)]
[0, 1, 4, 9, 16, 25, 36, 49, 64, 81]
```

This is much easier to read, and we no longer need to use a lambda. We have placed a `for` loop within square brackets. Let us now filter out the odd squares. We will show you how to do it with `map()` and `filter()` first, before then using a list comprehension again:

```
# even.squares.py
# using map and filter
sq1 = list(
    map(lambda n: n**2, filter(lambda n: not n % 2, range(10)))
)
# equivalent, but using list comprehensions
sq2 = [n**2 for n in range(10) if not n % 2]
print(sq1, sq1 == sq2)  # prints: [0, 4, 16, 36, 64] True
```

We think that the difference in readability is now evident. The list comprehension reads much better. It is almost English: give us all squares (`n**2`) for `n` between 0 and 9 if `n` is even.

According to the Python documentation (`https://docs.python.org/3.12/tutorial/datastructures.html#list-comprehensions`), the following is true:

> *A list comprehension consists of brackets containing an expression followed by a for clause, then zero or more for or if clauses. The result will be a new list resulting from evaluating the expression in the context of the for and if clauses which follow it.*

Nested comprehensions

Let us see an example of nested loops. This is quite common because many algorithms involve iterating on a sequence using two placeholders. The first one runs through the whole sequence, left to right. The second one does, too, but it starts from the first one, instead of 0. The concept is that of testing all pairs without duplication. Let us see the classical `for` loop equivalent:

```
# pairs.for.loop.py
items = "ABCD"
pairs = []
for a in range(len(items)):
```

```
    for b in range(a, len(items)):
        pairs.append((items[a], items[b]))
```

If you print `pairs` at the end, you get the following:

```
$ python pairs.for.loop.py
[('A', 'A'), ('A', 'B'), ('A', 'C'), ('A', 'D'), ('B', 'B'), ('B', 'C'),
('B', 'D'), ('C', 'C'), ('C', 'D'), ('D', 'D')]
```

All the tuples with the same letter are those where `b` is at the same position as `a`. Now, let us see how we can translate this to a list comprehension:

```
# pairs.list.comprehension.py
items = "ABCD"
pairs = [
    (items[a], items[b])
    for a in range(len(items))
    for b in range(a, len(items))
]
```

Notice that because the `for` loop over `b` depends on `a`, it must come after the `for` loop over `a` in the comprehension. If you swap them around, you will get a name error.

Another way of achieving the same result is to use the `combinations_with_replacement()` function from the `itertools` module (which we briefly introduced in *Chapter 3*, *Conditionals and Iteration*). You can read more about it in the official Python documentation.

Filtering a comprehension

We can also apply filtering to a comprehension. Let us first do it with `filter()`, and find all Pythagorean triples whose short sides are numbers smaller than 10. A **Pythagorean triple** is a triple *(a, b, c)* of integer numbers satisfying the equation $a^2 + b^2 = c^2$.

We obviously do not want to test a combination twice, and therefore, we will use a trick similar to the one we saw in the previous example:

```
# pythagorean.triple.py
from math import sqrt

# this will generate all possible pairs
```

```
mx = 10
triples = [
    (a, b, sqrt(a**2 + b**2))
    for a in range(1, mx)
    for b in range(a, mx)
]
# this will filter out all non-Pythagorean triples
triples = list(
    filter(lambda triple: triple[2].is_integer(), triples)
)
print(triples)  # prints: [(3, 4, 5.0), (6, 8, 10.0)]
```

In the preceding code, we generated a list of *three-tuples*, `triples`. Each tuple contains two integer numbers (the legs), and the hypotenuse of the Pythagorean triangle, whose legs are the first two numbers in the tuple. For example, when `a` is `3` and `b` is `4`, the tuple will be `(3, 4, 5.0)`, and when `a` is `5` and `b` is `7`, the tuple will be `(5, 7, 8.602325267042627)`.

After generating all the `triples`, we need to filter out all those where the hypotenuse is not an integer number. To achieve this, we filter based on `float_number.is_integer()` being `True`. This means that of the two example tuples we just showed you, the one with hypotenuse `5.0` will be retained, while the one with the `8.602325267042627` hypotenuse will be discarded.

This is good, but we do not like the fact that the triple has two integer numbers and a float—they are all supposed to be integers. We can use `map()` to fix this:

```
# pythagorean.triple.int.py
from math import sqrt

mx = 10
triples = [
    (a, b, sqrt(a**2 + b**2))
    for a in range(1, mx)
    for b in range(a, mx)
]
triples = filter(lambda triple: triple[2].is_integer(), triples)
# this will make the third number in the tuples integer
triples = list(
    map(lambda triple: triple[:2] + (int(triple[2]),), triples)
)
print(triples)  # prints: [(3, 4, 5), (6, 8, 10)]
```

Notice the step we added. We slice each element in `triples`, taking only the first two elements. Then, we concatenate the slice with a one-tuple, containing the integer version of that float number that we did not like. This code is getting quite complicated. We can achieve the same result with a much simpler list comprehension:

```
# pythagorean.triple.comprehension.py
from math import sqrt

# this step is the same as before
mx = 10
triples = [
    (a, b, sqrt(a**2 + b**2))
    for a in range(1, mx)
    for b in range(a, mx)
]
# here we combine filter and map in one CLEAN list comprehension
triples = [
    (a, b, int(c)) for a, b, c in triples if c.is_integer()
]
print(triples)  # prints: [(3, 4, 5), (6, 8, 10)]
```

That is cleaner, easier to read, and shorter. There is still room for improvement, though. We are still wasting memory by constructing a list with many triples that we end up discarding. We can fix that by combining the two comprehensions into one:

```
# pythagorean.triple.walrus.py
from math import sqrt

# this step is the same as before
mx = 10
# We can combine generating and filtering in one comprehension
triples = [
    (a, b, int(c))
    for a in range(1, mx)
    for b in range(a, mx)
    if (c := sqrt(a**2 + b**2)).is_integer()
]
print(triples)  # prints: [(3, 4, 5), (6, 8, 10)]
```

Now that is elegant. By generating the triples and filtering them in the same list comprehension, we avoid keeping any triple that does not pass the test in memory. Notice that we used an `assignment expression` to avoid needing to compute the value of `sqrt(a**2 + b**2)` twice.

Dictionary comprehensions

Dictionary comprehensions work exactly like list comprehensions, but to construct dictionaries. There is only a slight difference in the syntax. The following example will suffice to explain everything you need to know:

```
# dictionary.comprehensions.py
from string import ascii_lowercase

lettermap = {c: k for k, c in enumerate(ascii_lowercase, 1)}
```

If you print `lettermap`, you will see the following:

```
$ python dictionary.comprehensions.py
{'a': 1, 'b': 2, 'c': 3, 'd': 4, 'e': 5, 'f': 6, 'g': 7, 'h': 8,
'i': 9, 'j': 10, 'k': 11, 'l': 12, 'm': 13, 'n': 14, 'o': 15,
'p': 16, 'q': 17, 'r': 18, 's': 19, 't': 20, 'u': 21, 'v': 22,
'w': 23, 'x': 24, 'y': 25, 'z': 26}
```

In the preceding code, we are enumerating the sequence of all lowercase ASCII letters (using the `enumerate` function). We then construct a dictionary with the resulting letter/number pairs as keys and values. Notice how the syntax is similar to the familiar dictionary syntax.

There is also another way to do the same thing:

```
lettermap = dict((c, k) for k, c in enumerate(ascii_lowercase, 1))
```

In this case, we are feeding a generator expression (we will talk more about these later in this chapter) to the `dict` constructor.

Dictionaries do not allow duplicate keys, as shown in the following example:

```
# dictionary.comprehensions.duplicates.py
word = "Hello"
swaps = {c: c.swapcase() for c in word}
print(swaps)  # prints: {'H': 'h', 'e': 'E', 'l': 'L', 'o': 'O'}
```

We create a dictionary with the letters of the string `"Hello"` as keys and the same letters, but with the case swapped, as values. Notice that there is only one `"l": "L"` pair. The constructor does not complain; it simply reassigns duplicates to the last value. Let us make this clearer with another example that assigns to each key its position in the string:

```
# dictionary.comprehensions.positions.py
word = "Hello"
positions = {c: k for k, c in enumerate(word)}
print(positions)  # prints: {'H': 0, 'e': 1, 'l': 3, 'o': 4}
```

Notice the value associated with the letter `l: 3`. The `l: 2` pair is not there; it has been overridden by `l: 3`.

Set comprehensions

Set comprehensions are similar to list and dictionary ones. Let us see one quick example:

```
# set.comprehensions.py
word = "Hello"
letters1 = {c for c in word}
letters2 = set(c for c in word)
print(letters1)  # prints: {'H', 'o', 'e', 'l'}
print(letters1 == letters2)  # prints: True
```

Notice how for set comprehensions, as for dictionaries, duplication is not allowed, and therefore the resulting set has only four letters. Also, notice that the expressions assigned to `letters1` and `letters2` produce equivalent sets.

The syntax used to create `letters1` is similar to that of a dictionary comprehension. You can spot the difference only by the fact that dictionaries require keys and values, separated by colons, while sets do not. For `letters2`, we fed a generator expression to the `set()` constructor.

Generators

Generators are based on the concept of *iteration*, as we said before, and they allow coding patterns that combine elegance with efficiency.

Generators are of two types:

- **Generator functions**: These are similar to regular functions, but instead of returning results through `return` statements, they use `yield`, which allows them to suspend and resume their state between each call.

- **Generator expressions**: These are similar to the list comprehensions we have seen in this chapter, but instead of returning a list, they return an object that produces results one by one.

Generator functions

Generator functions behave like regular functions in all respects, except for one difference: instead of collecting results and returning them at once, they are automatically turned into iterators that yield results one at a time.

Suppose we asked you to count from 1 to 1,000,000. You start, and at some point, we ask you to stop. After some time, we ask you to resume. As long as you can remember the last number you reached, you will be able to continue where you left off. For example, if we stopped you after 31,415, you would just go on with 31,416, and so on. The point is that you do not need to remember all the numbers you said before 31,415, nor do you need them to be written down somewhere. Generators behave in much the same way.

Take a good look at the following code:

```
# first.n.squares.py
def get_squares(n): # classic function approach
    return [x**2 for x in range(n)]

print(get_squares(10))

def get_squares_gen(n):  # generator approach
    for x in range(n):
        yield x**2  # we yield, we do not return

print(list(get_squares_gen(10)))
```

The result of the two `print` statements will be the same: `[0, 1, 4, 9, 16, 25, 36, 49, 64, 81]`. But there is an important difference between the two functions. `get_squares()` is a classic function that collects all the squares of numbers in *[0, n)* in a list, and returns it. On the other hand, `get_squares_gen()` is a generator and behaves differently. Each time the interpreter reaches the `yield` line, its execution is suspended. The only reason those `print` statements return the same result is because we fed `get_squares_gen()` to the `list()` constructor, which exhausts the generator completely by asking for the next element until a `StopIteration` is raised. Let us see this in detail:

```
# first.n.squares.manual.py
def get_squares_gen(n):
    for x in range(n):
        yield x**2

squares = get_squares_gen(4)  # this creates a generator object
print(squares)  # <generator object get_squares_gen at 0x10dd...>
print(next(squares))  # prints: 0
print(next(squares))  # prints: 1
print(next(squares))  # prints: 4
print(next(squares))  # prints: 9
# the following raises StopIteration, the generator is exhausted,
# any further call to next will keep raising StopIteration
print(next(squares))
```

Each time we call `next()` on the generator object, we either start it (the first `next()`) or make it resume from the last suspension point (any other `next()`). The first time we call `next()` on it, we get 0, which is the square of 0, then 1, then 4, then 9, and since the `for` loop stops after that (`n` is 4), the generator naturally ends. A classic function would at that point just return `None`, but to comply with the iteration protocol, a generator will instead raise a `StopIteration` exception.

This explains how a `for` loop works. When you call `for k in range(n)`, what happens under the hood is that the `for` loop gets an iterator out of `range(n)` and starts calling `next` on it, until `StopIteration` is raised, which tells the `for` loop that the iteration has reached its end.

Having this behavior built into every iteration aspect of Python makes generators even more powerful because once we have written them, we will be able to plug them into whatever iteration mechanism we want.

At this point, you are probably asking yourself why you would want to use a generator instead of a regular function. The answer is to save time and (especially) memory.

We will talk more about performance later, but for now, let us concentrate on one aspect: sometimes, generators allow you to do something that would not be possible with a simple list. For example, say you want to analyze all permutations of a sequence. If the sequence has a length of *N*, then the number of its permutations is *N!*. This means that if the sequence is 10 elements long, the number of permutations is 3,628,800. But a sequence of 20 elements would have 2,432,902,008,176,640,000 permutations. They grow factorially.

Now imagine you have a classic function that is attempting to calculate all permutations, put them in a list, and return it to you. With 10 elements, it would require probably a few seconds, but for 20 elements there is simply no way that it could be done (it would take thousands of years and require billions of gigabytes of memory).

On the other hand, a generator function will be able to start the computation and give you back the first permutation, then the second, and so on. Of course, you will not have the time to process them all—there are too many—but at least you will be able to work with some of them. Sometimes the amount of data you have to iterate over is so huge that you cannot keep it all in memory in a list. In this case, generators are invaluable: they make possible that which otherwise would not be.

So, to save memory (and time), use generator functions whenever possible.

It is also worth noting that you can use the `return` statement in a generator function. It will cause a `StopIteration` exception to be raised, effectively ending the iteration. If a `return` statement were to make the function return something, it would break the iteration protocol. Python's consistency prevents this and allows us great ease when coding. Let us see a quick example:

```
# gen.yield.return.py
def geometric_progression(a, q):
    k = 0
    while True:
        result = a * q**k
        if result <= 100000:
            yield result
        else:
            return
        k += 1

for n in geometric_progression(2, 5):
    print(n)
```

The preceding code yields all terms of the geometric progression, *a, aq, aq2, aq3, ...*. When the progression produces a term that is greater than 100,000, the generator stops (with a `return` statement). Running the code produces the following result:

```
$ python gen.yield.return.py
2
10
50
```

```
250
1250
6250
31250
```

The next term would have been `156250`, which is too big.

Going beyond next

Generator objects have methods that allow us to control their behavior: `send()`, `throw()`, and `close()`. The `send()` method allows us to communicate a value back to the generator object, while `throw()` and `close()`, respectively, allow us to raise an exception within the generator and close it. Their use is quite advanced, and we will not be covering them here in detail, but we want to spend a few words on `send()`, with a simple example:

```
# gen.send.preparation.py
def counter(start=0):
    n = start
    while True:
        yield n
        n += 1

c = counter()
print(next(c))  # prints: 0
print(next(c))  # prints: 1
print(next(c))  # prints: 2
```

The preceding iterator creates a generator object that will run forever. You can keep calling it, and it will never stop. But what if you wanted to stop it at some point? One solution is to use a global variable to control the `while` loop:

```
# gen.send.preparation.stop.py
stop = False
def counter(start=0):
    n = start
    while not stop:
        yield n
        n += 1

c = counter()
```

```
print(next(c))  # prints: 0
print(next(c))  # prints: 1
stop = True
print(next(c))  # raises StopIteration
```

We initially set `stop = False`, and until we change it to `True`, the generator will just keep going, like before. After we change `stop` to `True` though, the `while` loop will exit, and the following call to `next` will raise a `StopIteration` exception. This trick works, but it is not a satisfactory solution. The function depends on an external variable, which can lead to problems. For example, the generator could inadvertently be stopped if another, unrelated function changes the global variable. Functions should ideally be self-contained and not rely on a global state.

The generator `send()` method takes a single argument, which is passed into the generator function as the value of the `yield` expression. We can use this to pass a flag value into the generator to signal that it should stop:

```
# gen.send.py
def counter(start=0):
    n = start
    while True:
        result = yield n  # A
        print(type(result), result)  # B
        if result == "Q":
            break
        n += 1

c = counter()
print(next(c))  # C
print(c.send("Wow!"))  # D
print(next(c))  # E
print(c.send("Q"))  # F
```

Executing this code produces the following output:

```
$ python gen.send.py
0
<class 'str'> Wow!
1
<class 'NoneType'> None
```

```
2
<class 'str'> Q
Traceback (most recent call last):
  File "gen.send.py", line 16, in <module>
    print(c.send("Q")) # F
          ^^^^^^^^^^^
StopIteration
```

We think it is worth going through this code line by line, as if we were executing it, to see whether we can understand what is going on.

We start the generator execution with a call to `next()` (`#C`). Within the generator, `n` is set to the same value as `start`. The `while` loop is entered, execution stops (`#A`), and `n` (`0`) is yielded back to the caller. `0` is printed on the console.

We then call `send()` (`#D`), execution resumes, `result` is set to `"Wow!"` (still `#A`), and its type and value are printed on the console (`#B`). `result` is not `"Q"`, so `n` is incremented by 1 and execution goes back to the top of the loop. The `while` condition is `True`, so another iteration of the loop is started. Execution again stops at `#A`, and `n` (`1`) is yielded back to the caller. `1` is printed on the console.

At this point, we call `next()` (`#E`), execution is resumed (`#A`), and because we are not sending anything to the generator explicitly, the `yield n` expression (`#A`) returns `None` (the behavior is the same as when we call a function that does not return anything). `result` is therefore set to `None`, and its type and value are again printed on the console (`#B`). Execution continues, `result` is not `"Q"`, so `n` is incremented by 1, and we start another loop again. Execution stops again (`#A`) and `n` (`2`) is yielded back to the caller. `2` is printed on the console.

Now we call `send` again (`#F`), this time passing the argument `"Q"`. The generator resumes, `result` is set to `"Q"` (`#A`), and its type and value are printed on the console again (`#B`). When we reach the `if` statement again, `result == "Q"` evaluates to `True`, and the `while` loop is stopped by the `break` statement. The generator naturally terminates, which means a `StopIteration` exception is raised. You can see the traceback of the exception in the last few lines printed on the console.

This is not at all simple to understand at first, so if it is not clear to you, do not be discouraged. You can keep reading and come back to this example later.

Using `send()` allows for interesting patterns, and it is worth noting that `send()` can also be used to start the execution of a generator (provided you call it with `None`).

The yield from expression

Another interesting construct is the `yield from` expression. This expression allows you to yield values from a sub-iterator. Its use allows for quite advanced patterns, so let us see a quick example of it:

```
# gen.yield.for.py
def print_squares(start, end):
    for n in range(start, end):
        yield n**2

for n in print_squares(2, 5):
    print(n)
```

The code above prints the numbers `4`, `9`, and `16` on the console (on separate lines). By now, we expect you to be able to understand it by yourself, but let us quickly recap what happens. The `for` loop outside the function gets an iterator from `print_squares(2, 5)` and calls `next()` on it until iteration is over. Every time the generator is called, execution is suspended (and later resumed) on `yield n**2`, which returns the square of the current `n`. Let us see how we could use a `yield from` expression to achieve the same result:

```
# gen.yield.from.py
def print_squares(start, end):
    yield from (n**2 for n in range(start, end))

for n in print_squares(2, 5):
    print(n)
```

This code produces the same result, but as you can see, `yield from` is actually running a sub-iterator, `(n**2 ...)`. The `yield from` expression returns to the caller each value the sub-iterator is producing. It is shorter and reads better.

Generator expressions

In addition to generator functions, generators can also be created using **generator expressions**. The syntax to create a generator expression is the same as for a list comprehension, except that we use round brackets instead of square brackets.

A generator expression will generate the same sequence of values as an equivalent list comprehensions. However, instead of immediately creating a list object containing the entire sequence in memory, the generator will yield the values one at a time. It is important to remember that you can only iterate over a generator once. After that, it will be exhausted.

Let us see an example:

```
# generator.expressions.txt
>>> cubes = [k**3 for k in range(10)]  # regular list
>>> cubes
[0, 1, 8, 27, 64, 125, 216, 343, 512, 729]
>>> type(cubes)
<class 'list'>
>>> cubes_gen = (k**3 for k in range(10))  # create as generator
>>> cubes_gen
<generator object <genexpr> at 0x7f08b2004860>
>>> type(cubes_gen)
<class 'generator'>
>>> list(cubes_gen)  # this will exhaust the generator
[0, 1, 8, 27, 64, 125, 216, 343, 512, 729]
>>> list(cubes_gen)  # nothing more to give
[]
```

As you can see from the output when we try to print it, `cubes_gen` is a generator object. To see the values it generates, we can use a `for` loop or a manual set of calls to `next`, or simply feed it to a `list()` constructor, which is what we did.

Notice how, once the generator has been exhausted, there is no way to recover the same elements from it again. We need to recreate it if we want to use it from scratch again.

In the next few examples, let us see how to reproduce `map()` and `filter()` using generator expressions. First, let's look at `map()`:

```
# gen.map.py
def adder(*n):
    return sum(n)

s1 = sum(map(adder, range(100), range(1, 101)))
s2 = sum(adder(*n) for n in zip(range(100), range(1, 101)))
```

In the previous example, `s1` and `s2` are both equal to the sum of `adder(0, 1)`, `adder(1, 2)`, `adder(2, 3)`, and so on, which translates to `sum(1, 3, 5, ...)`. We find the generator expression syntax to be much more readable, though.

Now for `filter()`:

```
# gen.filter.py
cubes = [x**3 for x in range(10)]
odd_cubes1 = filter(lambda cube: cube % 2, cubes)
odd_cubes2 = (cube for cube in cubes if cube % 2)
```

In this example, `odd_cubes1` and `odd_cubes2` are equivalent: they generate a sequence of odd cubes. Yet again, we prefer the generator syntax. This should be evident when things get a little more complicated:

```
# gen.map.filter.py
N = 20
cubes1 = map(
    lambda n: (n, n**3),
    filter(lambda n: n % 3 == 0 or n % 5 == 0, range(N)),
)
cubes2 = ((n, n**3) for n in range(N) if n % 3 == 0 or n % 5 == 0)
```

The preceding code creates two iterators, `cubes1` and `cubes2`. Both will yield the same sequence of tuples *(n, n3)* where `n` is a multiple of 3 or 5. If you print the list of values obtained from either, you get the following: `[(0, 0), (3, 27), (5, 125), (6, 216), (9, 729), (10, 1000), (12, 1728), (15, 3375), (18, 5832)]`.

Notice that the generator expression is much easier to read. It may be debatable for trivial examples, but as soon as you start performing more complex operations, the superiority of the generator syntax is evident. It is shorter, simpler, and more elegant.

Now, let us ask you: what is the difference between the following lines of code?

```
# sum.example.py
s1 = sum([n**2 for n in range(10**6)])
s2 = sum((n**2 for n in range(10**6)))
s3 = sum(n**2 for n in range(10**6))
```

Strictly speaking, they all produce the same sum. The expressions to get `s2` and `s3` are equivalent because the brackets in `s2` are redundant. Both are generator expressions passed to the `sum()` function.

The expression to get `s1` is different, though. Here we are passing the result of a list comprehension to `sum()`. This wastes both time and memory because we first create a list of a million elements (which has to be stored in memory). We then pass the list to `sum`, which iterates over it, after which we discard the list. It is much better to use a generator expression, as we do not need to wait for a list to be constructed, and we do not need to store the entire sequence of 1 million values in memory.

So, *watch out for extra parentheses when you write your expressions*. Details like this are easy to miss, but they can make a significant difference. For example, look at the following code:

```
# sum.example.2.py
s = sum([n**2 for n in range(10**10)])  # this is killed
# s = sum(n**2 for n in range(10**10))  # this succeeds
print(s)  # prints: 333333333283333333335000000000
```

If we run this, we get:

```
$ python sum.example.2.py
Killed
```

On the other hand, if we comment out the first line, and uncomment the second one, this is the result:

```
$ python sum.example.2.py
333333333283333333335000000000
```

The difference between the two lines is that in the first, the Python interpreter must construct a list with the squares of the first ten billion numbers to pass to the `sum` function. That list is huge, and we ran out of memory, so the operating system killed the process.

When we remove the square brackets, we no longer have a list. The `sum` function receives a generator, which yields 0, 1, 4, 9, and so on, and computes the sum without needing to keep all the values in memory.

Some performance considerations

There are usually multiple ways of achieving the same result. We can use any combination of `map()`, `zip()`, and `filter()`, or choose to go with a comprehension or a generator. We may even decide to go with `for` loops. Readability is often a factor in choosing between these approaches. List comprehensions or generator expressions are often easier to read than complex combinations of `map()` and `filter()`. For more complicated operations, generator functions or `for` loops are often better.

Besides readability concerns, however, we must also consider performance when deciding which approach to use. There are two factors that need to be considered when comparing the performance of different implementations: `space` and `time`.

Space refers to the amount of memory that your data structures are going to use. The best way to choose is to ask yourself if you really need a list (or tuple), or whether a generator would work instead.

If the answer is yes to the latter, go with the generator, as it will save a lot of space. The same goes for functions: if you do not actually need them to return a list or tuple, then you can transform them into generator functions as well.

Sometimes, you will have to use lists (or tuples); for example, there are algorithms that scan sequences using multiple pointers, and others need to iterate over the sequence more than once. A generator (function or expression) can be iterated over only once before it is exhausted, so in these situations, it would not be the right choice.

Time is a bit more complicated than space because it depends on more variables, and it is not always possible to state that *X is faster than Y* with absolute certainty for all cases. However, based on tests run on Python today, we can say that on average, `map()` exhibits performance similar to comprehensions and generator expressions, while `for` loops are consistently slower.

To appreciate the reasoning behind these statements fully, we need to understand how Python works, which is a bit outside the scope of this book as it is quite technical and detailed. Let us just say that `map()` and comprehensions run at C language speed within the interpreter, while a Python `for` loop is run as Python bytecode within the Python Virtual Machine, which is often much slower.

There are several different implementations of Python. The original one, and still the most common one, is CPython (`https://github.com/python/cpython`), which is written in C. C is one of the most powerful and popular programming languages still used today.

In the rest of this section, we will perform some simple experiments to verify these performance claims. We will write a small piece of code that collects the results of `divmod(a, b)` for a set of integer pairs, `(a, b)`. We will use the `time()` function from the `time` module to calculate the elapsed time of the operations that we perform:

```
# performance.py
from time import time
mx = 5000
t = time()  # start time for the for loop
floop = []
for a in range(1, mx):
    for b in range(a, mx):
        floop.append(divmod(a, b))
print("for loop: {:.4f} s".format(time() - t))  # elapsed time

t = time()  # start time for the list comprehension
compr = [divmod(a, b) for a in range(1, mx) for b in range(a, mx)]
print("list comprehension: {:.4f} s".format(time() - t))

t = time()  # start time for the generator expression
gener = list(
    divmod(a, b) for a in range(1, mx) for b in range(a, mx)
)
print("generator expression: {:.4f} s".format(time() - t))
```

As you can see, we are creating three lists: `floop`, `compr`, and `gener`. Running the code produces the following:

```
$ python performance.py
for loop: 2.3832 s
list comprehension: 1.6882 s
generator expression: 1.6525 s
```

The list comprehension runs in ~71% of the time taken by the `for` loop. The generator expression was slightly faster than that, with ~69%. The difference in time between the list comprehension and generator expression is hardly significant, and if you re-run the example a few times, you will probably also see the list comprehension take less time than the generator expression.

It is worth noting that, within the body of the `for` loop, we are appending data to a list. This implies that, behind the scenes, the Python interpreter occasionally has to resize the list to allocate space for more items to be appended. We guessed that creating a list of zeros, and simply filling it with the results, might have sped up the `for` loop, but we were wrong. Try it for yourself; you just need `mx * (mx - 1) // 2` elements to be pre-allocated.

The approach we used here for timing execution is rather naïve. In *Chapter 11*, *Debugging and Profiling*, we will look at better ways of profiling code and timing execution.

Let us see a similar example that compares a `for` loop and a `map()` call:

```
# performance.map.py
from time import time

mx = 2 * 10**7

t = time()
absloop = []
for n in range(mx):
    absloop.append(abs(n))
print("for loop: {:.4f} s".format(time() - t))

t = time()
abslist = [abs(n) for n in range(mx)]
print("list comprehension: {:.4f} s".format(time() - t))

t = time()
absmap = list(map(abs, range(mx)))

print("map: {:.4f} s".format(time() - t))
```

This code is conceptually similar to the previous example. The only thing that has changed is that we are applying the `abs()` function instead of `divmod()`, and we have only one loop instead of two nested ones. Execution gives the following result:

```
$ python performance.map.py
for loop: 1.9009 s
list comprehension: 1.0973 s
map: 0.5862 s
```

This time, `map` was the fastest: it took ~53% of the time required by the list comprehension, and ~31% of the time needed by the `for` loop.

The results from these experiments give us a rough indication of the relative speed of `for` loops, list comprehensions, generator expressions, and the `map()` function. Do not rely too heavily on these results though, as the experiments we performed here are rather simplistic, and accurately measuring and comparing execution times is difficult. Measurements can easily be affected by several factors, such as other processes running on the same computer. Performance results are also heavily dependent on the hardware, operating system, and Python version.

It is clear that `for` loops are slower than comprehensions or `map()`, so it is worth discussing why we nevertheless often prefer them over the alternatives.

Do not overdo comprehensions and generators

We have seen how powerful comprehensions and generator expressions can be. However, we find that the more you try to do within a single comprehension or generator expression, the harder it becomes to read, understand, and therefore maintain or change.

If you consider the Zen of Python again, there are a few lines that, we think, are worth keeping in mind when dealing with optimized code:

```
>>> import this
...
Explicit is better than implicit.
Simple is better than complex.
...
Readability counts.
...
If the implementation is hard to explain, it's a bad idea.
...
```

Comprehensions and generator expressions are more implicit than explicit, can be quite difficult to read and understand, and can be difficult to explain. Sometimes, you have to break them apart using the inside-out technique to understand what is going on.

To give you an example, let us talk a bit more about Pythagorean triples. Just to remind you, a Pythagorean triple is a tuple of positive integers *(a, b, c)* such that $a^2 + b^2 = c^2$. We saw how to calculate them in the *Filtering a comprehension* section, but we did it in a very inefficient way. We scanned all pairs of numbers below a certain threshold, calculating the hypotenuse, and filtering out those that were not valid Pythagorean triples.

A better way to get a list of Pythagorean triples is to generate them directly. There are many different formulas you can use to do this; here we will use the **Euclidean formula**. This formula says that any triple *(a, b, c)*, where $a = m^2 - n^2$, $b = 2mn$ and $c = m^2 + n^2$, with *m* and *n* positive integers such that $m > n$, is a Pythagorean triple. For example, when $m = 2$ and $n = 1$, we find the smallest triple: *(3, 4, 5)*.

There is one catch though: consider the triple *(6, 8, 10)*, which is like *(3, 4, 5)*, only all the numbers are multiplied by *2*. This triple is Pythagorean, since $6^2 + 8^2 = 10^2$, but we can derive it from *(3, 4, 5)* simply by multiplying each of its elements by *2*. The same goes for *(9, 12, 15)*, *(12, 16, 20)*, and in general for all the triples that we can write as *(3k, 4k, 5k)*, with *k* being a positive integer greater than *1*.

A triple that cannot be obtained by multiplying the elements of another one by some factor, *k*, is called **primitive**. Another way of stating this is as follows: if the three elements of a triple are **coprime**, then the triple is primitive. Two numbers are coprime when they do not share any prime factor among their divisors, that is, when their **greatest common divisor** (**GCD**) is *1*. For example, 3 and 5 are coprime, while 3 and 6 are not because they are both divisible by 3.

The Euclidean formula tells us that if *m* and *n* are coprime, and $m - n$ is odd, the triple they generate is *primitive*. In the following example, we will write a generator expression to calculate all the primitive Pythagorean triples whose hypotenuse, *c*, is less than or equal to some integer, *N*. This means we want all triples for which $m^2 + n^2 \leq N$. When *n* is *1*, the formula looks like this: $m^2 \leq N - 1$, which means we can approximate the calculation with an upper bound of $m \leq N^{1/2}$.

To recap: *m* must be greater than *n*, they must also be coprime, and their difference $m - n$ must be odd. Moreover, to avoid useless calculations, we will put the upper bound for *m* at *floor(sqrt(N)) + 1*.

The `floor` function for a real number, *x*, gives the maximum integer, *n*, such that $n < x$, for example, *floor(3.8) = 3*, *floor(13.1) = 13*. Taking *floor(sqrt(N)) + 1* means taking the integer part of the square root of *N* and adding a minimal margin just to make sure we do not miss any numbers.

Let us put all of this into code, step by step. We start by writing a simple `gcd()` function that uses **Euclid's algorithm**:

```
# functions.py
def gcd(a, b):
    """Calculate the Greatest Common Divisor of (a, b)."""
    while b != 0:
```

```
        a, b = b, a % b
    return a
```

The explanation of Euclid's algorithm is available on the web, so we will not spend any time talking about it here as we need to focus on the generator expression. The next step is to use the knowledge we gathered before to generate a list of primitive Pythagorean triples:

```
# pythagorean.triple.generation.py
from functions import gcd
N = 50
triples = sorted(  # 1
    (
        (a, b, c) for a, b, c in (  # 2
            ((m**2 - n**2), (2 * m * n), (m**2 + n**2))  # 3
            for m in range(1, int(N**.5) + 1)  # 4
            for n in range(1, m)  # 5
            if (m - n) % 2 and gcd(m, n) == 1  # 6
        )
        if c <= N  # 7
    ),
    key=sum  # 8
)
```

This is not easy to read, so let us go through it line by line. At `#3`, we start a generator expression that creates triples. You can see from `#4` and `#5` that we are looping on `m` in *[1, M]*, with *M* being the integer part of *sqrt(N)*, plus *1*. On the other hand, `n` loops within *[1, m)*, to respect the $m > n$ rule. It is worth noting how we calculated *sqrt(N)*, that is, `N**.5`, which is just another way to do it that we wanted to show you.

At `#6`, you can see the filtering conditions to make the triples primitive: `(m - n) % 2` evaluates to `True` when `(m - n)` is odd, and `gcd(m, n) == 1` means `m` and `n` are coprime. With these in place, we know the triples will be primitive. This takes care of the innermost generator expression. The outermost one starts at `#2` and finishes at `#7`. We take the triples `(a, b, c) in (...innermost generator...)` such that `c <= N`.

Finally, at `#1`, we apply sorting to present the list in order. At `#8`, after the outermost generator expression is closed, you can see that we specify the sorting key to be the sum `a + b + c`. This is just our personal preference; there is no mathematical reason behind it.

This code is certainly not easy to understand or explain. Code like this is also difficult to debug or modify. It should have no place in a professional environment.

Let us see whether we can rewrite this code into something more readable:

```
# pythagorean.triple.generation.for.py
from functions import gcd
def gen_triples(N):
    for m in range(1, int(N**.5) + 1):  # 1
        for n in range(1, m):  # 2
            if (m - n) % 2 and gcd(m, n) == 1:  # 3
                c = m**2 + n**2  # 4
                if c <= N:  # 5
                    a = m**2 - n**2  # 6
                    b = 2 * m * n  # 7
                    yield (a, b, c)  # 8
triples = sorted(gen_triples(50), key=sum)  # 9
```

This is much easier to read. Let us go through it, line by line. You will see it is also much easier to understand.

We start looping at `#1` and `#2`, over the same ranges as in the previous example. On line `#3`, we filter for primitive triples. On line `#4`, we deviate a bit from what we were doing before: we calculate `c`, and on line `#5`, we filter on `c` being less than or equal to `N`. We only calculate `a` and `b`, and yield the resulting tuple if `c` satisfies that condition. We could have calculated the values of `a` and `b` earlier, but by delaying until we know all conditions for a valid triple are satisfied, we avoid wasting time and CPU cycles. On the last line, we apply sorting with the same key we were using in the generator expression example.

We hope you agree that this example is easier to understand. If we ever need to modify the code, this will be much easier, and less error-prone to work with, than the generator expression.

If you print the results of both examples, you will get this:

```
[(3, 4, 5), (5, 12, 13), (15, 8, 17), (7, 24, 25), (21, 20, 29), (35, 12,
37), (9, 40, 41)]
```

There is often a trade-off between performance and readability, and it is not always easy to get the balance right. Our advice is to try to use comprehensions and generator expressions whenever you can. But if the code starts to become complicated to modify or difficult to read or explain, you may want to refactor it into something more readable.

Name localization

Now that we are familiar with all types of comprehensions and generator expressions, let us talk about name localization within them. Python 3 localizes loop variables in all four forms of comprehensions: list, dictionary, set, and generator expressions. This behavior is different from that of the `for` loop. Let us look at some simple examples to show all the cases:

```
# scopes.py
A = 100
ex1 = [A for A in range(5)]
print(A)  # prints: 100

ex2 = list(A for A in range(5))
print(A)  # prints: 100

ex3 = {A: 2 * A for A in range(5)}
print(A)  # prints: 100

ex4 = {A for A in range(5)}
print(A)  # prints: 100

s = 0
for A in range(5):
    s += A
print(A)  # prints: 4
```

In the preceding code, we declare a global name, `A = 100`. We then have list, dictionary, and set comprehensions, and a generator expression. Even though they all use the name `A`, none of them alter the global name, `A`. On the other hand, the `for` loop at the end does modify the global `A`. The last `print` statement prints 4.

Let us see what happens if the global `A` was not there:

```
# scopes.noglobal.py
ex1 = [A for A in range(5)]
print(A)  # breaks: NameError: name 'A' is not defined
```

The preceding code would work in the same way with any other type of comprehension or with a generator expression. After we run the first line, `A` is not defined in the global namespace. Once again, the `for` loop behaves differently:

```
# scopes.for.py
s = 0
for A in range(5):
    s += A
print(A) # prints: 4
print(globals())
```

The preceding code shows that after a `for` loop, if the loop variable was not defined before it, we can find it in the global namespace. We can verify this by inspecting the dictionary returned by the `globals()` built-in function:

```
$ python scopes.for.py
4
{'__name__': '__main__', '__doc__': None, ..., 's': 10, 'A': 4}
```

Along with various built-in global names (which we have not reproduced here), we see `'A': 4`.

Generation behavior in built-ins

Generator-like behavior is quite common among the built-in types and functions. This is a major difference between Python 2 and Python 3. In Python 2, functions such as `map()`, `zip()`, and `filter()` returned lists instead of iterable objects. The idea behind this change is that if you need to make a list of those results, you can always wrap the call in a `list()` class. On the other hand, if you just need to iterate and want to keep the impact on memory as light as possible, you can use those functions safely. Another notable example is the `range()` function. In Python 2, it returned a list, and there was another function called `xrange()` that behaved like the `range()` function now behaves in Python 3.

The idea of functions and methods that return iterable objects is quite widespread. You can find it in the `open()` function, which is used to operate on file objects (we will see it in *Chapter 8*, *Files and Data Persistence*), but also in `enumerate()`, in the dictionary `keys()`, `values()`, and `items()` methods, and several other places.

It all makes sense: Python aims to reduce the memory footprint by avoiding wasting space wherever possible, especially in those functions and methods that are used extensively in most situations.

At the beginning of this chapter, we said that it makes more sense to optimize the performance of code that has to deal with large collections of objects, rather than shaving off a few milliseconds from a function that we call twice a day. That is precisely what Python itself is doing here.

One last example

Before we finish this chapter, we will show you a simple problem that Fabrizio used to give to candidates for a Python developer role in a company he used to work for.

The problem is the following: write a function that returns the terms of the sequence *0 1 1 2 3 5 8 13 21 ...*, up to some limit, *N*.

If you have not recognized it, that is the Fibonacci sequence, which is defined as $F(0) = 0$, $F(1) = 1$ and, for any $n > 1$, $F(n) = F(n-1) + F(n-2)$. This sequence is excellent for testing knowledge about recursion, memoization techniques, and other technical details, but in this case, it was a good opportunity to check whether the candidate knew about generators.

Let us start with a rudimentary version, and then improve on it:

```
# fibonacci.first.py
def fibonacci(N):
    """Return all fibonacci numbers up to N."""
    result = [0]
    next_n = 1
    while next_n <= N:
        result.append(next_n)
        next_n = sum(result[-2:])
    return result

print(fibonacci(0))  # [0]
print(fibonacci(1))  # [0, 1, 1]
print(fibonacci(50))  # [0, 1, 1, 2, 3, 5, 8, 13, 21, 34]
```

From the top: we set up the `result` list to a starting value of `[0]`. Then we start the iteration from the next element (`next_n`), which is 1. While the next element is not greater than `N`, we keep appending it to the list and calculating the next value in the sequence. We calculate the next element by taking a slice of the last two elements in the `result` list and passing it to the `sum` function.

If you struggle to understand the code, it can help to add some `print()` statements so that you can see how values change during execution.

When the loop condition evaluates to `False`, we exit the loop and return `result`. You can see the result of those `print` statements in the comments next to each of them.

At this point, Fabrizio would ask the candidate the following question: *What if I just wanted to iterate over those numbers?* A good candidate would then change the code to the following:

```
# fibonacci.second.py
def fibonacci(N):
    """Return all fibonacci numbers up to N."""
    yield 0
    if N == 0:
        return
    a = 0
    b = 1
    while b <= N:
        yield b
        a, b = b, a + b

print(list(fibonacci(0)))  # [0]
print(list(fibonacci(1)))  # [0, 1, 1]
print(list(fibonacci(50)))  # [0, 1, 1, 2, 3, 5, 8, 13, 21, 34]
```

This is actually one of the solutions he was given. Now, the `fibonacci()` function is a *generator function*. First, we yield 0, and then, if `N` is 0, we `return` (this will cause a `StopIteration` exception to be raised). If that is not the case, we start looping, yielding `b` at every iteration, before updating `a` and `b`. This solution relies on the fact that we only need the last two elements (`a` and `b`) to be able to produce the next one.

This code is much better, has a lighter memory footprint, and all we have to do to get a list of Fibonacci numbers is wrap the call with `list()`, as usual. We can make it even more elegant, though:

```
# fibonacci.elegant.py
def fibonacci(N):
    """Return all fibonacci numbers up to N."""
    a, b = 0, 1
    while a <= N:
        yield a
        a, b = b, a + b
```

The whole body of the function is now only four lines, or five if you count the docstring. Notice how, in this case, using tuple assignment (`a, b = 0, 1` and `a, b = b, a + b`) helps in making the code shorter and more readable.

Summary

In this chapter, we explored the concepts of iteration and generation a bit more deeply. We looked at the `map()`, `zip()`, and `filter()` functions in detail, and learned how to use them as an alternative to a regular `for` loop approach.

Then, we covered the concept of comprehensions to construct lists, dictionaries, and sets. We explored their syntax and how to use them as an alternative to both the classic `for` loop approach and the `map()`, `zip()`, and `filter()` functions.

Finally, we talked about the concept of generators in two forms: generator functions and expressions. We learned how to save time and space by using generation techniques. We also saw how operations that are infeasible to perform with lists can be performed with generators instead.

We talked about performance and saw that `for` loops come last in terms of speed, but they provide the best readability and flexibility to change. On the other hand, functions such as `map()` and `filter()`, and comprehensions, can be much faster.

The complexity of the code written using these techniques grows exponentially, so to favor readability and ease of maintainability, we still need to use the classic `for` loop approach at times. Another difference is in the name localization, where the `for` loop behaves differently from all other types of comprehensions.

The next chapter will be all about objects and classes. It is structurally similar to this one, in that we will not explore many different subjects—just a few of them—but we will try to delve deeper into them.

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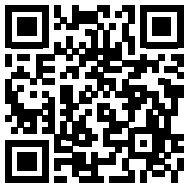

6

OOP, Decorators, and Iterators

> *"La classe non è acqua." ("Class will out.")*
>
> *—Italian saying*

Object-oriented programming (OOP) is such a vast topic that entire books have been written about it. In this chapter, we face the challenge of finding the balance between breadth and depth. There are simply too many things to discuss, and plenty of them would take more than this whole chapter if we described them in depth. Therefore, we will try to give you what we think is a good panoramic view of the fundamentals, plus a few things that may come in handy in the next chapters. Python's official documentation will help to fill the gaps.

In this chapter, we are going to cover the following topics:

- Decorators
- OOP with Python
- Iterators

Decorators

In *Chapter 5*, *Comprehensions and Generators*, we measured the execution time of various expressions.

If you recall, we had to capture the start time and subtract it from the current time after execution to calculate the elapsed time. We also printed it on the console after each measurement. That was impractical.

Every time we find ourselves repeating things, an alarm bell should go off. Can we put that code in a function and avoid repetition? Most of the time, the answer is, *yes*, so let us look at an example:

```
# decorators/time.measure.start.py
from time import sleep, time

def f():
    sleep(0.3)

def g():
    sleep(0.5)

t = time()
f()
print("f took:", time() - t)  # f took: 0.3028988838195801

t = time()
g()
print("g took:", time() - t)  # g took: 0.507941722869873
```

In the preceding code, we defined two functions, `f()` and `g()`, which do nothing but sleep (for 0.3 and 0.5 seconds, respectively). We used the `sleep()` function to suspend the execution for the desired amount of time. Notice how the time measure is pretty accurate. Now, how do we avoid repeating that code and those calculations? One first potential approach could be the following:

```
# decorators/time.measure.dry.py
from time import sleep, time

def f():
    sleep(0.3)

def g():
    sleep(0.5)

def measure(func):
    t = time()
    func()
    print(func.__name__, "took:", time() - t)
```

```
measure(f)  # f took: 0.3043971061706543
measure(g)  # g took: 0.5050859451293945
```

Much better. The whole timing mechanism has been encapsulated in a function, so we do not repeat code. We print the function name dynamically and the code is straightforward. What if we needed to pass any arguments to the function we measure? This code would get just a bit more complex. Let us see an example:

```
# decorators/time.measure.arguments.py
from time import sleep, time

def f(sleep_time=0.1):
    sleep(sleep_time)

def measure(func, *args, **kwargs):
    t = time()
    func(*args, **kwargs)
    print(func.__name__, "took:", time() - t)

measure(f, sleep_time=0.3)  # f took: 0.30092811584472656
measure(f, 0.2)  # f took: 0.20505475997924805
```

Now, `f()` expects to be fed `sleep_time` (with a default value of 0.1), so we do not need `g()` anymore. We also had to change the `measure()` function so that it now accepts a function, any variable positional arguments, and any variable keyword arguments. This way, whatever we call `measure()` with, we redirect those arguments to the call to `func()` that we do inside.

This is good, but we can improve it a little. Let us say that we somehow want to have that timing behavior built into the `f()` function, enabling us to just call it and have that measure taken. Here is how we could do it:

```
# decorators/time.measure.deco1.py
from time import sleep, time

def f(sleep_time=0.1):
    sleep(sleep_time)

def measure(func):
    def wrapper(*args, **kwargs):
```

```
        t = time()
        func(*args, **kwargs)
        print(func.__name__, "took:", time() - t)

    return wrapper

f = measure(f)  # decoration point

f(0.2)  # f took: 0.20128178596496582
f(sleep_time=0.3)  # f took: 0.30509519577026367
print(f.__name__)  # wrapper  <- ouch!
```

The preceding code is not so straightforward. Let us see what happens here. The magic is in the *decoration point*. We reassign `f()` with whatever is returned by `measure()` when we call it with `f()` as an argument. Within `measure()`, we define another function, `wrapper()`, and then we return it. So the net effect is that after the decoration point, when we call `f()`, we are actually calling `wrapper()` (you can witness this in the last line of code). Since the `wrapper()` inside calls `func()`, which in this case is a reference to `f()`, we close the loop.

The `wrapper()` function is, not surprisingly, a wrapper. It takes variable positional and keyword arguments and calls `f()` with them. It also does the time measurement calculation around the call.

This technique is called **decoration**, and `measure()` is, effectively, a **decorator**. This paradigm became so popular and widely used that, in version 2.4, Python added a special syntax for it. You can read the specifics in PEP 318 (`https://peps.python.org/pep-0318/`). In Python 3.0, we saw PEP 3129 (`https://peps.python.org/pep-3129/`) defining class decorators. Finally, in Python 3.9, the decorator syntax was slightly amended to relax some grammar restrictions; this change was brought about in PEP 614 (`https://peps.python.org/pep-0614/`).

Let us now explore three cases: one decorator, two decorators, and one decorator that takes arguments. First, the single decorator case:

```
# decorators/syntax.py
def func(arg1, arg2, ...):
    pass
func = decorator(func)

# is equivalent to the following:
```

```
@decorator
def func(arg1, arg2, ...):
    pass
```

Instead of manually reassigning the function to what was returned by the decorator, we prepend the definition of the function with the special syntax, `@decorator_name`.

We can apply multiple decorators to the same function in the following way:

```
# decorators/syntax.py
def func(arg1, arg2, ...):
    pass
func = deco1(deco2(func))

# is equivalent to the following:

@deco1
@deco2
def func(arg1, arg2, ...):
    pass
```

When applying multiple decorators, it is important to pay attention to the order. In the preceding example, `func()` is decorated with `deco2()` first, and the result is decorated with `deco1()`. A good rule of thumb is *the closer the decorator is to the function, the sooner it is applied*.

Before we give you another example, let us fix the issue with the function name. Take a look at the highlighted section in the following code:

```
# decorators/time.measure.deco1.py
def measure(func):
    def wrapper(*args, **kwargs):
        …
    return wrapper

f = measure(f)  # decoration point
print(f.__name__)  # wrapper  <- ouch!
```

We don't want to lose the original function's name and docstring when we decorate it. But because `f`, the decorated function, is reassigned to `wrapper`, its original attributes are lost, replaced with those of `wrapper()`. There is an easy fix for that from the `functools` module. We will fix the issue and rewrite the code to use the `@` operator:

```
# decorators/time.measure.deco2.py
from time import sleep, time
from functools import wraps

def measure(func):
    @wraps(func)
    def wrapper(*args, **kwargs):
        t = time()
        func(*args, **kwargs)
        print(func.__name__, "took:", time() - t)
    return wrapper

@measure
def f(sleep_time=0.1):
    """I'm a cat. I love to sleep!"""
    sleep(sleep_time)

f(sleep_time=0.3)  # f took: 0.30042004585266113
print(f.__name__)  # f
print(f.__doc__ )  # I'm a cat. I love to sleep!
```

All looks good. As you can see, all we need to do is to tell Python that `wrapper` actually wraps `func()` (by means of the `wraps()` function in the highlighted portion of the code above), and you can see that the original name and docstring are maintained.

For the full list of function attributes that are reassigned by `func()`, please check the official documentation for the `functools.update_wrapper()` function here: `https://docs.python.org/3/library/functools.html?#functools.update_wrapper`.

Let us see another example. We want a decorator that prints an error message when the result of a function is greater than a certain threshold. We will also take this opportunity to show you how to apply two decorators at once:

```
# decorators/two.decorators.py
from time import time
from functools import wraps

def measure(func):
    @wraps(func)
    def wrapper(*args, **kwargs):
        t = time()
        result = func(*args, **kwargs)
        print(func.__name__, "took:", time() - t)
        return result
    return wrapper

def max_result(func):
    @wraps(func)
    def wrapper(*args, **kwargs):
        result = func(*args, **kwargs)
        if result > 100:
            print(
                f"Result is too big ({result}). "
                "Max allowed is 100."
            )
        return result
    return wrapper

@measure
@max_result
def cube(n):
    return n**3

print(cube(2))
print(cube(5))
```

We had to enhance the `measure()` decorator so that its `wrapper()` now returns the result of the call to `func()`. The `max_result()` decorator does that as well, but before returning, it checks that `result` is not greater than `100`, which is the maximum allowed.

We decorated `cube()` with both of them. First, `max_result()` is applied, and then `measure()`. Running this code yields this result:

```
$ python two.decorators.py
cube took: 9.5367431640625e-07
8

Result is too big (125). Max allowed is 100.
cube took: 3.0994415283203125e-06
125
```

For your convenience, we have separated the results of the two calls with a blank line. In the first call, the result is 8, which passes the threshold check. The running time is measured and printed. Finally, we print the result (8).

On the second call, the result is 125, so the error message is printed and the result returned; then it is the turn of `measure()`, which prints the running time again, and finally, we print the result (125).

Had we decorated the `cube()` function with the same two decorators but in a different order, the order of the printed messages would also have been different.

A decorator factory

Some decorators can take arguments. This technique is generally used to produce another decorator (in which case, the object could be called a **decorator factory**). Let us look at the syntax, and then we will see an example of it:

```
# decorators/syntax.py
def func(arg1, arg2, ...):
    pass

func = decoarg(arg_a, arg_b)(func)

# is equivalent to the following:

@decoarg(arg_a, arg_b)
def func(arg1, arg2, ...):
    pass
```

As you can see, this case is a bit different. First, `decoarg()` is called with the given arguments, and then its return value (the actual decorator) is called with `func()`.

Let us improve on the example now. We are going back to a single decorator: `max_result()`. We want to make it so that we can decorate different functions with different thresholds, as we do not want to have to write one decorator for each threshold. Therefore, let us amend `max_result()` so that it allows us to decorate functions by specifying the threshold dynamically:

```
# decorators/decorators.factory.py
from functools import wraps

def max_result(threshold):
    def decorator(func):
        @wraps(func)
        def wrapper(*args, **kwargs):
            result = func(*args, **kwargs)
            if result > threshold:
                print(
                    f"Result is too big ({result})."
                    f"Max allowed is {threshold}."
                )
            return result
        return wrapper
    return decorator

@max_result(75)
def cube(n):
    return n**3
```

The preceding code shows you how to write a decorator factory. If you recall, decorating a function with a decorator that takes arguments is the same as writing `func = decorator(argA, argB)(func)`, so when we decorate `cube()` with `max_result(75)`, we are doing `cube = max_result(75)(cube)`.

Let us go through what happens, step by step. When we call `max_result(75)`, we enter its body. A `decorator()` function is defined inside the `max_result(75)` function, which takes a function as its only argument. Inside that function, we find the usual decoration pattern. We define `wrapper()`, inside of which we check the result of the original function's call. The beauty of this approach is that from the innermost level, we can still refer to both `func()` and `threshold`, which allows us to set the threshold dynamically.

The `wrapper()` function returns `result`, `decorator()` returns `wrapper()`, and `max_result()` returns `decorator()`. This means that the `cube = max_result(75)(cube)` instruction actually becomes `cube = decorator(cube)`. However, it's not just any `decorator()` but one for which `threshold` has a value of `75`. This is achieved by a mechanism called **closure**.

Dynamically created functions that are returned by other functions are called **closures**. Their main feature is that they have full access to the variables and names defined in the local namespace at the time of their creation, even though the enclosing in which they were defined has returned and finished executing.

Running the last example produces the following result:

```
$ python decorators.factory.py
Result is too big (125). Max allowed is 75.
125
```

The preceding code allows us to use the `max_result()` decorator with different thresholds, like this:

```
# decorators/decorators.factory.py
@max_result(75)
def cube(n):
    return n**3

@max_result(100)
def square(n):
    return n**2

@max_result(1000)
def multiply(a, b):
    return a * b
```

Note that every decoration uses a different `threshold` value.

Decorators are very popular in Python. They are used quite often, and they make code simpler and more elegant.

OOP

Now that the basics of the decoration pattern have been covered, it is time to explore OOP. We will use the definition from *Kindler, E.; Krivy, I. (2011). Object-oriented simulation of systems with sophisticated control (International Journal of General Systems)*, and adapt it to Python:

> **Object-oriented programming (OOP)** *is a programming paradigm based on the concept of "objects," which are data structures that contain data, in the form of attributes, and code, in the form of functions known as methods. A distinguishing feature of objects is that an object's method can access and often modify the data attributes of the object with which they are associated (objects have a notion of "self"). In OO programming, computer programs are designed by making them out of objects that interact with one another.*

Python has full support for this paradigm. Actually, as we have already said, *everything in Python is an object*, so this shows that OOP is not just supported by Python but is also a core feature of the language.

The two main players in OOP are **objects** and **classes**. Classes are used to create objects, and we say that objects are **instances** of classes.

If you struggle to understand the difference between objects and classes, think of it like this. When you hear the word "pen," you know exactly what the type (or class) of object that the word represents is. However, if we say "this pen," then we're not referring to a class of objects but, rather, to an "instance" of that class: a real object.

When objects are created from a class, they inherit the class attributes and methods. They represent concrete items in the program's domain.

The simplest Python class

We will start with the simplest class you could ever write in Python:

```
# oop/simplest.class.py
class Simplest:
    pass

print(type(Simplest))  # what type is this object?

simp = Simplest()  # we create an instance of Simplest: simp
print(type(simp))  # what type is simp?
# is simp an instance of Simplest?
print(type(simp) is Simplest)  # There's a better way to do this
```

Let us run the preceding code and explain it line by line:

```
$ python simplest.class.py
<class 'type'>
<class '__main__.Simplest'>
True
```

The `Simplest` class we defined has only the `pass` instruction in its body, which means it doesn't have any custom attributes or methods. We will print its type (`__main__` is the name of the scope in which top-level code executes), and we are aware that, in the highlighted comment, we wrote *object* instead of *class*. As you can see by the result of that `print` statement, *classes are in fact objects themselves*. To be precise, they are instances of `type`. Explaining this concept would lead us to a talk about **metaclasses** and **metaprogramming**, advanced concepts that require a solid grasp of the fundamentals to be understood and are beyond the scope of this chapter. As usual, we mentioned it to leave a pointer for you, for when you are ready to explore more deeply.

Let us go back to the example: we created `simp`, an instance of the `Simplest` class. You can see that the syntax to create an instance is the same as the syntax for calling a function. Next, we print what type `simp` belongs to, and we verify that `simp` is, in fact, an instance of `Simplest`. We will show you a better way of doing this later on in the chapter.

So far, it has all been very simple. However, what happens when we write `class ClassName(): pass`? Well, what Python does is to create a class object and assign it a name. This is very similar to what happens when we declare a function using `def`.

Class and object namespaces

After a class object has been created (which usually happens when the module is first imported), it represents a namespace. We can call that class to create its instances. Each instance inherits the class attributes and methods and is given its own namespace. We already know that in order to walk a namespace, all we need to do is to use the dot (`.`) operator.

Let us look at another example:

```
# oop/class.namespaces.py
class Person:
    species = "Human"

print(Person.species)  # Human
Person.alive = True  # Added dynamically!
print(Person.alive)  # True
```

```
man = Person()
print(man.species)  # Human (inherited)
print(man.alive)  # True (inherited)

Person.alive = False
print(man.alive)  # False (inherited)

man.name = "Darth"
man.surname = "Vader"
print(man.name, man.surname)  # Darth Vader
```

In the preceding example, we defined a **class attribute** called `species`. Any name defined in the body of a class becomes an attribute that belongs to that class. In the code, we also defined `Person.alive`, which is another class attribute. You can see that there is no restriction on accessing that attribute from the class. You can see that `man`, which is an instance of `Person`, inherits both of them, reflecting them instantly when they change.

The `man` instance also has two attributes that belong to its own namespace and are, therefore, called **instance attributes**: `name` and `surname`.

Class attributes are shared among all instances, while **instance attributes** are not; therefore, you should use class attributes to provide the states and behaviors to be shared by all instances, and use instance attributes for data that will be specific to each individual object.

Attribute shadowing

When you search for an attribute on an object and cannot find it, Python extends the search to the attributes on the object's class (and keeps searching until the attribute is either found or the end of the inheritance chain is reached—more on inheritance later). This leads to an interesting shadowing behavior. Let us look at an example:

```
# oop/class.attribute.shadowing.py
class Point:
    x = 10
    y = 7

p = Point()
```

```
print(p.x)  # 10 (from class attribute)
print(p.y)  # 7 (from class attribute)

p.x = 12  # p gets its own `x` attribute
print(p.x)  # 12 (now found on the instance)
print(Point.x)  # 10 (class attribute still the same)

del p.x  # we delete instance attribute
print(p.x)  # 10 (now search has to go again to find class attr)

p.z = 3  # let's make it a 3D point
print(p.z)  # 3

print(Point.z)
# AttributeError: type object 'Point' has no attribute 'z'
```

The preceding code is interesting. We defined a class called `Point` with two class attributes, `x` and `y`. When we create an instance of `Point`, `p`, you can see that we can access both `x` and `y` from the `p` namespace (`p.x` and `p.y`). What happens when we do that is that Python doesn't find any `x` or `y` attributes on the instance, and therefore, it searches the class and finds them there.

Then, we give `p` its own `x` attribute by assigning `p.x = 12`. This behavior may appear a bit weird at first, but if you think about it, it is exactly the same as what happens in a function that declares `x = 12` when there is a global `x = 10` outside (see the section about scopes in *Chapter 4*, *Functions, the Building Blocks of Code*, for a refresher). We know that `x = 12` won't affect the global one, and for class and instance attributes, it is exactly the same.

After assigning `p.x = 12`, when we print it, the search does not need to reach the class attributes because `x` is found on the instance, so we get `12` printed out. We also print `Point.x`, which refers to `x` in the class namespace, to show that it is still 10.

Then, we delete `x` from the namespace of `p`, which means that, on the next line, when we print it again, Python will have to search for it in the class because it is no longer found on the instance.

The last three lines show you that assigning attributes to an instance doesn't mean that they will be found in the class. Instances get whatever is in the class, but the opposite is not true.

What do you think about putting the `x` and `y` coordinates as class attributes? Do you think it was a good idea? What if we created another instance of `Point`? Would that help to show why instance attributes are needed?

The self argument

From within a class method, we can refer to an instance by means of a special argument, called `self` by convention. `self` is always the first attribute of an instance method. Let us examine this behavior, together with how we can share not just attributes but also methods with all instances:

```
# oop/class.self.py
class Square:
    side = 8

    def area(self):  # self is a reference to an instance
        return self.side**2

sq = Square()
print(sq.area())  # 64 (side is found on the class)
print(Square.area(sq))  # 64 (equivalent to sq.area())

sq.side = 10
print(sq.area())  # 100 (side is found on the instance)
```

Note how the `area()` method is used by `sq`. The two calls, `Square.area(sq)` and `sq.area()`, are equivalent, and they teach us how the mechanism works. Either you pass the instance to the method call (`Square.area(sq)`), which within the method will take the name `self`, or you can use a more comfortable syntax, `sq.area()`, and Python will translate that for you behind the scenes.

Let us look at a better example:

```
# oop/class.price.py
class Price:
    def final_price(self, vat, discount=0):
        """Returns price after applying vat and fixed discount."""
        return (self.net_price * (100 + vat) / 100) - discount

p1 = Price()
p1.net_price = 100
print(Price.final_price(p1, 20, 10))  # 110 (100 * 1.2 - 10)
print(p1.final_price(20, 10))  # equivalent
```

The preceding code shows us that nothing prevents us from using arguments when declaring methods. We can use the exact same syntax as we used with the function, but we need to remember that the first argument will always be the instance that the method will be bound to. We don't need to necessarily call it `self`, but it is the convention, and this is one of the few cases where it is very important to abide by it.

Initializing an instance

Have you noticed how, before calling `p1.final_price()` in the code above, we had to assign `net_price` to `p1`? There is a better way to do it. In other languages, this would be called a **constructor**, but in Python, it is not. It is actually an **initializer**, since it works on an already created instance, and therefore, it is called `__init__()`. It is a **magic method**, which is run right after the object is created. Python objects also have a `__new__()` method, which is the actual constructor. However, in practice, it is not so common to have to override it; that is a technique that is mostly used when writing metaclasses. Let us now see an example of how to initialize objects in Python:

```
# oop/class.init.py
class Rectangle:
    def __init__(self, side_a, side_b):
        self.side_a = side_a
        self.side_b = side_b

    def area(self):
        return self.side_a * self.side_b

r1 = Rectangle(10, 4)
print(r1.side_a, r1.side_b)  # 10 4
print(r1.area())  # 40

r2 = Rectangle(7, 3)
print(r2.area())  # 21
```

Things are finally starting to take shape. When an object is created, the `__init__()` method is run for us automatically. In this case, we wrote it so that when we create a `Rectangle` object (by calling the class name like a function), we pass arguments to the creation call, like we would on any regular function call. The way we pass parameters follows the signature of the `__init__()` method, and therefore, in the two creation statements, `10` and `4` will be `side_a` and `side_b` for `r1`, while `7` and `3` will be `side_a` and `side_b` for `r2`. You can see that the call to `area()` from `r1` and `r2` reflects that they have different instance arguments. Setting up objects in this way is more convenient.

OOP is about code reuse

By now, it should be clear: *OOP is all about code reuse*. We define a class, we create instances, and those instances can use the methods that are defined in the class. They will behave differently according to how the instances have been set up by the initializer.

Inheritance and composition

However, this is just half of the story; OOP is more than just this. We have two main design constructs to use: inheritance and composition.

Inheritance means that two objects are related by means of an **Is-A** type of relationship. On the other hand, **composition** means that two objects are related by means of a **Has-A** relationship. Let us explain with an example, where we declare classes for engine types:

```
# oop/class_inheritance.py
class Engine:
    def start(self):
        pass

    def stop(self):
        pass

class ElectricEngine(Engine):  # Is-A Engine
    pass

class V8Engine(Engine):  # Is-A Engine
    pass
```

Then, we want to declare some car types that will use those engines:

```
class Car:
    engine_cls = Engine

    def __init__(self):
        self.engine = self.engine_cls()  # Has-A Engine

    def start(self):
        print(
            f"Starting {self.engine.__class__.__name__} for "
```

```
            f"{self.__class__.__name__}... Wroom, wroom!"
        )
        self.engine.start()

    def stop(self):
        self.engine.stop()

class RaceCar(Car):  # Is-A Car
    engine_cls = V8Engine

class CityCar(Car):  # Is-A Car
    engine_cls = ElectricEngine

class F1Car(RaceCar):  # Is-A RaceCar and also Is-A Car
    pass  # engine_cls same as parent

car = Car()
racecar = RaceCar()
citycar = CityCar()
f1car = F1Car()
cars = [car, racecar, citycar, f1car]

for car in cars:
    car.start()
```

Running the above prints the following:

```
$ python class_inheritance.py
Starting Engine for Car... Wroom, wroom!
Starting V8Engine for RaceCar... Wroom, wroom!
Starting ElectricEngine for CityCar... Wroom, wroom!
Starting V8Engine for F1Car... Wroom, wroom!
```

The preceding example shows you both the **Is-A** and **Has-A** types of relationships. First of all, let us consider `Engine`. It is a simple class with two methods, `start()` and `stop()`. We then define `ElectricEngine` and `V8Engine`, which both inherit from it. You can see this from their definition, which includes `Engine` within brackets after the name.

This means that both `ElectricEngine` and `V8Engine` inherit attributes and methods from the `Engine` class, which is said to be their **base class** (or **parent class**).

The same happens with cars. `Car` is a base class for both `RaceCar` and `CityCar`. `RaceCar` is also the base class of `F1Car`. Another way of saying this is that `F1Car` inherits from `RaceCar`, which inherits from `Car`. Therefore, `F1Car` *Is-A* `RaceCar`, and `RaceCar` *Is-A* `Car`. Because of the transitive property, we can say that `F1Car` *Is-A* `Car` as well. `CityCar`, too, *Is-A* `Car`.

When we define `class A(B): pass`, we say that `A` is the *child* of `B`, and `B` is the *parent* of `A`. The *parent* and *base* classes are synonyms, and so are *child of* and *derived from*. Also, we say that a class *inherits* from another class, or that it *extends* it.

This is the inheritance mechanism.

Let us now go back to the code. Each class has a class attribute, `engine_cls`, which is a reference to the engine class that we want to assign to each type of car. `Car` has a generic `Engine`, the two race cars have a V8 engine, and the city car has an electric one.

When a car is created in the initializer method, `__init__()`, we create an instance of whatever engine class is assigned to the car and set it as the `engine` instance attribute.

It makes sense to have `engine_cls` shared among all class instances because it is quite likely that all instances of the same car class will have the same kind of engine. On the other hand, it would not be good to have a single engine (an instance of any `Engine` class) as a class attribute because that would mean sharing one engine among all car instances, which is incorrect.

The type of relationship between a car and its engine is a *Has-A* type. A car *Has-A* engine. This is called **composition** and reflects the fact that objects can be composed of many other objects. A car *Has-A* engine, gears, wheels, a frame, doors, seats, and so on.

When using OOP, it is important to describe objects in this way so that we can properly structure our code.

Notice that we had to avoid having dots in the `class_inheritance.py` script name, as dots in module names make imports difficult. Most modules in the source code of the book are meant to be run as standalone scripts, so we chose to add dots to enhance readability when possible, but in general, you want to avoid dots in your module names.

Before we leave this paragraph, let us verify the correctness of what we stated above with another example:

```
# oop/class.issubclass.isinstance.py
from class_inheritance import Car, RaceCar, F1Car

car = Car()
racecar = RaceCar()
f1car = F1Car()
cars = [(car, "car"), (racecar, "racecar"), (f1car, "f1car")]
car_classes = [Car, RaceCar, F1Car]

for car, car_name in cars:
    for class_ in car_classes:
        belongs = isinstance(car, class_)
        msg = "is a" if belongs else "is not a"
        print(car_name, msg, class_.__name__)

""" Prints:
… (starting enging messages omitted)
car is a Car
car is not a RaceCar
car is not a F1Car
racecar is a Car
racecar is a RaceCar
racecar is not a F1Car
f1car is a Car
f1car is a RaceCar
f1car is a F1Car
"""
```

As you can see, `car` is just an instance of `Car`, while `racecar` is an instance of `RaceCar` (and by extension of `Car`), and `f1car` is an instance of `F1Car` (and of both `RaceCar` and `Car`, by extension). Similarly, a *banana* is an instance of *Banana*. But, also, it is a *Fruit*. Also, it is *Food*, right? Same concept. To check whether an object is an instance of a class, use the `isinstance()` function. It is recommended over sheer type comparison (`type(object) is Class`).

Notice that we have left out the prints you get when instantiating the cars. We saw them in the previous example.

Let us also check inheritance. Same setup, but different logic in the `for` loops:

```
# oop/class.issubclass.isinstance.py
for class1 in car_classes:
    for class2 in car_classes:
        is_subclass = issubclass(class1, class2)
        msg = "{0} a subclass of".format(
            "is" if is_subclass else "is not"
        )
        print(class1.__name__, msg, class2.__name__)

""" Prints:
Car is a subclass of Car
Car is not a subclass of RaceCar
Car is not a subclass of F1Car
RaceCar is a subclass of Car
RaceCar is a subclass of RaceCar
RaceCar is not a subclass of F1Car
F1Car is a subclass of Car
F1Car is a subclass of RaceCar
F1Car is a subclass of F1Car
"""
```

Interestingly, we learn that *a class is a subclass of itself*. Check the output of the preceding example to see that it matches the explanation we provided.

Note that, by convention, class names are written using *CapWords*, which means *ThisWayIsCorrect*, as opposed to functions and methods, which are written in snake case, like *this_way_is_correct*. Also, if you want to use a name in your code that clashes with a Python-reserved keyword or a built-in function or class, the convention is to add a trailing underscore to the name. In the first *for loop* example, we loop through the class names using `for class_ in ...` because `class` is a reserved word. You can refresh your knowledge about conventions by reading PEP 8.

To help illustrate the difference between *Is-A* and *Has-A*, look at the following diagram:

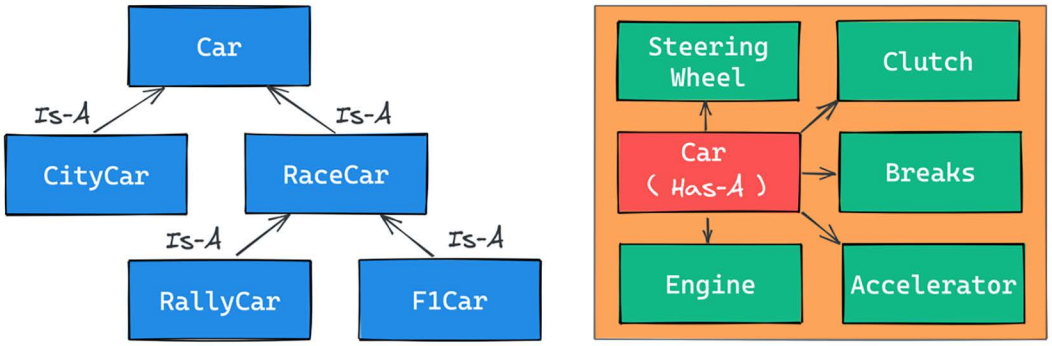

Figure 6.1: Is-A versus Has-A relationships

Accessing a base class

We have already seen class declarations, such as `class ClassA: pass` and `class ClassB(BaseClassName): pass`. When we don't specify a base class explicitly, Python will set the built-in **object** class as the base class. Ultimately, all classes derive from `object`. Please remember that, if you do not specify a base class, brackets are optional and, in practice, are never used.

Therefore, writing `class A: pass` or `class A(): pass` or `class A(object): pass` are all equivalent. The `object` class is a special class in that it hosts the methods that are common to all Python classes, and it does not allow you to set any attributes on it.

Let us see how we can access a base class from within a class:

```
# oop/super.duplication.py
class Book:
    def __init__(self, title, publisher, pages):
        self.title = title
        self.publisher = publisher
        self.pages = pages

class Ebook(Book):
    def __init__(self, title, publisher, pages, format_):
        self.title = title
        self.publisher = publisher
        self.pages = pages
        self.format_ = format_
```

Take a look at the preceding code. Three of the input parameters for `Book` are duplicated in `Ebook`. This is bad practice because we now have two sets of instructions that are doing the same thing. Moreover, any change in the signature of `Book.__init__()` will not be reflected in `Ebook`. Normally, we want changes in a base class to be reflected in its children. Let us see one way to fix this issue:

```
# oop/super.explicit.py
class Book:
    def __init__(self, title, publisher, pages):
        self.title = title
        self.publisher = publisher
        self.pages = pages

class Ebook(Book):
    def __init__(self, title, publisher, pages, format_):
        Book.__init__(self, title, publisher, pages)
        self.format_ = format_

ebook = Ebook(
    "Learn Python Programming", "Packt Publishing", 500, "PDF"
)
print(ebook.title)  # Learn Python Programming
print(ebook.publisher)  # Packt Publishing
print(ebook.pages)  # 500
print(ebook.format_)  # PDF
```

Much better. We have removed that code duplication. In this example, we tell Python to call the `__init__()` method of the `Book` class; we feed `self` to that call, making sure that we bind it to the present instance.

If we modify the logic within the `__init__()` method of `Book`, we do not need to touch `Ebook`; the change will transfer automatically.

This approach is good, but it still suffers from a minor issue. Say that we change the name of `Book` to `Liber`, which is the Latin word for "book." We would then have to change the `__init__()` method of `Ebook` to reflect that change. This can be avoided by using `super`:

```
# oop/super.implicit.py
class Book:
    def __init__(self, title, publisher, pages):
        self.title = title
```

```
        self.publisher = publisher
        self.pages = pages

class Ebook(Book):
    def __init__(self, title, publisher, pages, format_):
        super().__init__(title, publisher, pages)
        # Another way to do the same thing is:
        # super(Ebook, self).__init__(title, publisher, pages)
        self.format_ = format_

ebook = Ebook(
    "Learn Python Programming", "Packt Publishing", 500, "PDF"
)
print(ebook.title)  # Learn Python Programming
print(ebook.publisher)  # Packt Publishing
print(ebook.pages)  # 500
print(ebook.format_)  # PDF
```

`super()` is a function that returns a proxy object that delegates method calls to a parent or sibling class.

Two classes are siblings if they share the same parents.

In this case, `super()` will delegate the call to `Book.__init__()`, and the beauty of this approach is that now we are free to change `Book` to `Liber` without having to touch the logic in the `__init__()` method of `Ebook` at all.

Now that we know how to access a base class from its child, let us explore Python's multiple inheritance.

Multiple inheritance

In Python, we are allowed to define classes that inherit from more than one base class. This is called **multiple inheritance**. When a class has more than one base class, attribute search can follow more than one path. Take a look at the following diagram:

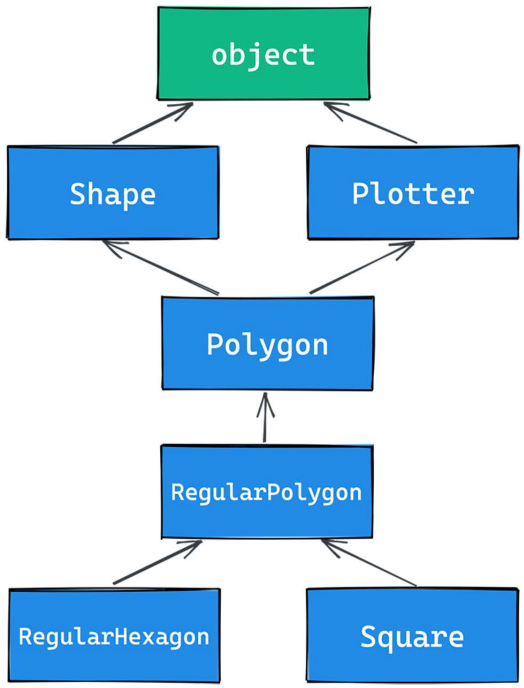

Figure 6.2: A class inheritance diagram

As you can see, `Shape` and `Plotter` act as base classes for all the others. `Polygon` inherits directly from them, `RegularPolygon` inherits from `Polygon`, and both `RegularHexagon` and `Square` inherit from `RegularPolygon`. Note also that `Shape` and `Plotter` implicitly inherit from `object`, so from `Polygon` up to `object`, we have what is known as a **diamond.** In simpler terms, we have more than one path to reach a base class. We will see why this matters in a few moments. Let us translate the diagram into code:

```
# oop/multiple.inheritance.py
class Shape:
    geometric_type = "Generic Shape"
    def area(self):  # This acts as placeholder for the interface
        raise NotImplementedError

    def get_geometric_type(self):
        return self.geometric_type

class Plotter:
    def plot(self, ratio, topleft):
```

```
        # Imagine some nice plotting logic here...
        print("Plotting at {}, ratio {}.".format(topleft, ratio))

class Polygon(Shape, Plotter):  # base class for polygons
    geometric_type = "Polygon"

class RegularPolygon(Polygon):  # Is-A Polygon
    geometric_type = "Regular Polygon"
    def __init__(self, side):
        self.side = side

class RegularHexagon(RegularPolygon):  # Is-A RegularPolygon
    geometric_type = "RegularHexagon"
    def area(self):
        return 1.5 * (3**0.5 * self.side**2)

class Square(RegularPolygon):  # Is-A RegularPolygon
    geometric_type = "Square"
    def area(self):
        return self.side * self.side

hexagon = RegularHexagon(10)
print(hexagon.area())  # 259.8076211353316
print(hexagon.get_geometric_type())  # RegularHexagon
hexagon.plot(0.8, (75, 77))  # Plotting at (75, 77), ratio 0.8.

square = Square(12)
print(square.area())  # 144
print(square.get_geometric_type())  # Square
square.plot(0.93, (74, 75))  # Plotting at (74, 75), ratio 0.93.
```

Take a look at the preceding code: the `Shape` class has one attribute, `geometric_type`, and two methods, `area()` and `get_geometric_type()`. It is quite common to use base classes (such as `Shape`, in our example) to define an **interface**, a set of methods for which children must provide an implementation. There are different and better ways to do this, but we want to keep this example as simple as possible for the time being.

We also have the `Plotter` class, which adds the `plot()` method, thereby providing plotting capabilities for any class that inherits from it. Of course, the `plot()` implementation is just a dummy `print()` in this example. The first interesting class is `Polygon`, which inherits from both `Shape` and `Plotter`.

There are many types of polygons, one of which is the regular one, which is both equiangular (all angles are equal) and equilateral (all sides are equal), so we create the `RegularPolygon` class that inherits from `Polygon`. For a regular polygon, where all sides are equal, we can implement a simple `__init__()` method, which just takes the length of the side. We create the `RegularHexagon` and `Square` classes, which both inherit from `RegularPolygon`.

This structure is quite long, but hopefully, it gives you an idea of how to specialize the classification of your objects.

Now, please take a look at the last eight lines of code. Note that when we call the `area()` method on `hexagon` and `square`, we get the correct area for both. This is because they both provide the correct implementation logic for it. Also, we can call `get_geometric_type()` on both of them, even though it is not defined in their classes, and Python goes all the way up to `Shape` to find an implementation for it. Note that, even though the implementation is provided in the `Shape` class, the `self.geometric_type()` used for the return value is correctly taken from the caller instance.

The `plot()` method calls are also interesting and show you how you can enrich your objects with capabilities they would not otherwise have. This technique is very popular in web frameworks such as Django, which provides special classes called **mixins**, whose capabilities you can just use out of the box. All you need is to define the desired mixin as one of the base classes for your class.

Multiple inheritance is powerful, but at the same time, it can get a bit messy, so we need to make sure we understand what happens when we use it.

Method resolution order

By now, we know that when we ask for `someobject.attribute` and `attribute` is not found on that object, Python starts searching in the class that `someobject` was created from. If it is not there either, Python searches up the inheritance chain until either `attribute` is found or the `object` class is reached. This is quite simple to understand if the inheritance chain is only made of single-inheritance steps, which means that classes have only one parent, all the way up to `object`. However, when multiple inheritance is involved, there are cases when it is not straightforward to predict which class will be searched next if an attribute is not found.

Python provides a way to always know the order in which classes are searched on attribute lookup: the **method resolution order** (**MRO**).

The MRO is the order in which base classes are searched for a member during lookup. Since version 2.3, Python uses an algorithm called **C3**, which guarantees monotonicity.

Let us see the MRO for the `Square` class from the previous example:

```
# oop/multiple.inheritance.py
print(square.__class__.__mro__)
# prints:
# (<class '__main__.Square'>, <class '__main__.RegularPolygon'>,
#  <class '__main__.Polygon'>, <class '__main__.Shape'>,
#  <class '__main__.Plotter'>, <class 'object'>)
```

To get to the MRO of a class, we can go from the instance to its `__class__` attribute, and from that to its `__mro__` attribute. Alternatively, we could have used `Square.__mro__`, or `Square.mro()` directly, but if you need to access the MRO from an instance, you will have to derive its class dynamically.

Note that the only point of doubt is the branching after `Polygon`, where the inheritance chain creates two paths: one leads to `Shape` and the other to `Plotter`. We know by scanning the MRO for the `Square` class that `Shape` is searched before `Plotter`.

Why is this important? Well, consider the following code:

```
# oop/mro.simple.py
class A:
    label = "a"

class B(A):
    label = "b"

class C(A):
    label = "c"

class D(B, C):
    pass
```

```
d = D()
print(d.label)  # Hypothetically this could be either 'b' or 'c'
```

Both `B` and `C` inherit from `A`, and `D` inherits from both `B` and `C`. This means that the lookup for the `label` attribute can reach the top (`A`) through either `B` or `C`. Depending on which is reached first, we get a different result.

In this preceding example, we get `'b'`, which is what we were expecting, since `B` is the leftmost among the base classes of `D`. But what happens if we remove the `label` attribute from `B`? This would be a confusing situation: will the algorithm go all the way up to `A` or will it get to `C` first? Let us find out:

```
# oop/mro.py
class A:
    label = "a"

class B(A):
    pass  # was: label = 'b'

class C(A):
    label = "c"

class D(B, C):
    pass

d = D()
print(d.label)  # 'c'
print(d.__class__.mro())  # notice another way to get the MRO
# prints:
# [<class '__main__.D'>, <class '__main__.B'>,
#  <class '__main__.C'>, <class '__main__.A'>, <class 'object'>]
```

So we learn that the MRO is `D->B->C->A->object`, which means that when we ask for `d.label`, we get `'c'`.

In day-to-day programming, it is not common to have to deal with the MRO, but we felt it was important to at least mention it in this paragraph so that, should you get entangled in a complex mixins structure, you will be able to find your way out of it.

Class and static methods

So far, we have written classes with attributes in the form of data and instance methods, but there are two other types of methods that we can find in a class definition: **static methods** and **class methods**.

Static methods

When you create a class object, Python assigns a name to it. That name acts as a namespace, and sometimes, it makes sense to group functionalities under it. Static methods are perfect for this use case. Unlike instance methods, they do not need to be passed an instance when called. Let us look at an example:

```
# oop/static.methods.py
class StringUtil:
    @staticmethod
    def is_palindrome(s, case_insensitive=True):
        # we allow only letters and numbers
        s = "".join(c for c in s if c.isalnum())  # Study this!
        # For case insensitive comparison, we lower-case s
        if case_insensitive:
            s = s.lower()
        for c in range(len(s) // 2):
            if s[c] != s[-c - 1]:
                return False
        return True

    @staticmethod
    def get_unique_words(sentence):
        return set(sentence.split())

print(
    StringUtil.is_palindrome("Radar", case_insensitive=False)
)  # False: Case Sensitive
print(StringUtil.is_palindrome("A nut for a jar of tuna"))  # True
print(StringUtil.is_palindrome("Never Odd, Or Even!"))  # True
print(
    StringUtil.is_palindrome(
        "In Girum Imus Nocte Et Consumimur Igni"
```

```
    )  # Latin palindrome
)  # True

print(
    StringUtil.get_unique_words(
        "I love palindromes. I really really love them!"
    )
)
# {'them!', 'palindromes.', 'I', 'really', 'love'}
```

The preceding code is quite interesting. First, we learn that static methods are created by simply applying the `staticmethod` decorator to them. You can see that they don't require any extra arguments, so apart from the decoration, they just look like functions.

We have a class, `StringUtil`, that acts as a container for functions. Another approach would be to have a separate module with functions inside. It is really a matter of style, most of the time.

The logic inside `is_palindrome()` should be straightforward for you by now, but just in case, let us go through it. First, we remove all characters from `s` that are neither letters nor numbers. We use the `join()` method of a string object to do this. By calling `join()` on an empty string, the result is that all elements in the iterable you pass to `join()` will be concatenated together. We feed `join()` a generator expression that produces all alphanumeric characters in `s` in order. This is a normal procedure when analyzing palindromes.

If `case_insensitive` is `True`, we lowercase `s`. Finally, we proceed to check whether `s` is a palindrome. To do this, we compare the first and last characters, then the second and the second to last, and so on. If, at any point, we find a difference, it means the string isn't a palindrome, and therefore, we can return `False`. On the other hand, if we exit the `for` loop normally, it means no differences were found, and we can, therefore, say the string is a palindrome.

Notice that this code works correctly regardless of the length of the string—that is, if the length is odd or even. The measure `len(s) // 2` reaches half of `s`, and if `s` is an odd number of characters long, the middle one won't be checked (for instance, in *RaDaR*, *D* is not checked), but we don't care, as it would be compared to itself.

The `get_unique_words()` method is much simpler: it just returns a set to which we feed a list with the words from a sentence. The `set` class removes any duplication for us, so we don't need to do anything else.

The `StringUtil` class provides us with a container namespace for methods that are meant to work on strings. Another example could have been a `MathUtil` class with some static methods to work on numbers.

Class methods

Class methods are slightly different from static methods in that, like instance methods, they also receive a special first argument. In their case, it is the class object itself, rather than the instance. A very common use case for class methods is to provide factory capability to a class, which means having alternative ways to create instances of the class. Let us see an example:

```
# oop/class.methods.factory.py
class Point:
    def __init__(self, x, y):
        self.x = x
        self.y = y

    @classmethod
    def from_tuple(cls, coords):  # cls is Point
        return cls(*coords)

    @classmethod
    def from_point(cls, point):  # cls is Point
        return cls(point.x, point.y)

p = Point.from_tuple((3, 7))
print(p.x, p.y)  # 3 7
q = Point.from_point(p)
print(q.x, q.y)  # 3 7
```

In the preceding code, we show you how to use a class method to create a factory for the `Point` class. In this case, we want to create a `Point` instance by passing both coordinates (regular creation `p = Point(3, 7)`), but we also want to be able to create an instance by passing a tuple (`Point.from_tuple()`) or another instance (`Point.from_point()`).

Within each class method, the `cls` argument refers to the `Point` class. As with the instance method, which takes `self` as the first argument, the class method takes a `cls` argument. Both `self` and `cls` are named after a convention that you are not forced to follow but are strongly encouraged to respect. This is something that no professional Python coder would change; it is so strong a convention that plenty of tools, such as parsers, linters, and the like, rely on it.

Class and static methods play well together. Static methods are particularly useful for breaking up the logic of a class method to improve its layout.

Let us see an example by refactoring the `StringUtil` class:

```
# oop/class.methods.split.py
class StringUtil:
    @classmethod
    def is_palindrome(cls, s, case_insensitive=True):
        s = cls._strip_string(s)
        # For case insensitive comparison, we lower-case s
        if case_insensitive:
            s = s.lower()
        return cls._is_palindrome(s)

    @staticmethod
    def _strip_string(s):
        return "".join(c for c in s if c.isalnum())

    @staticmethod
    def _is_palindrome(s):
        for c in range(len(s) // 2):
            if s[c] != s[-c - 1]:
                return False
        return True

    @staticmethod
    def get_unique_words(sentence):
        return set(sentence.split())

print(StringUtil.is_palindrome("radar"))  # True
print(StringUtil.is_palindrome("not a palindrome"))  # False
```

Compare this code with the previous version. First of all, note that even though `is_palindrome()` is now a class method, we call it in the same way we called it when it was a static one. The reason why we changed it to a class method is that after factoring out some of its logic (to `_strip_string()` and `_is_palindrome()`), we need to get a reference to those methods, and if we have no `cls` in our method, the only option would be to call them by using the name of the class itself, like so: `StringUtil._strip_string()` and `StringUtil._is_palindrome()`.

However, this is not good practice because we would hardcode the class name in the `is_palindrome()` method, thereby putting ourselves in the position of having to modify it whenever we want to change the class name. Using `cls` means it will act as the class name, which means our code won't need any modifications should the class name change.

Notice how the new logic reads much better than the previous version. Moreover, notice that, by naming the *factored-out* methods with a leading underscore, we hint that those methods are not supposed to be called from outside the class, but this will be the subject of the next paragraph.

Private methods and name mangling

If you have any background in languages like Java, C#, or C++, then you know that they allow the programmer to assign a privacy status to attributes (both data and methods). Each language has its own slightly different flavor for this, but the gist is that public attributes are accessible from any point in the code, while private ones are accessible only within the scope they are defined in.

In Python, there is no such thing. Everything is public; therefore, we rely on conventions and, for privacy, on a mechanism called **name mangling**.

The convention is as follows: if an attribute's name has no leading underscores, it is considered public. This means you can access it and modify it freely. When the name has one leading underscore, the attribute is considered private, which means it is intended to be used internally, and you should not modify it or call it from the outside. A very common use case for private attributes is helper methods that are supposed to be used by public ones (possibly in call chains in conjunction with other methods). Another use case is internal data, such as scaling factors, or any other data that we would ideally put in a constant, a variable that, once defined, cannot change. However, Python has no concept of constants.

We know some programmers who don't feel at ease with this aspect of Python. In our experience, we have never encountered situations in which we had bugs because Python lacks private attributes. It is a matter of discipline, best practices, and following conventions.

The amount of freedom Python offers to a developer is the reason why, sometimes, it is referred to as a *language for adults*. And of course, there are pros and cons to every design choice. At the end of the day, some people prefer languages that allow more power and might require a bit more responsibility, while others prefer languages that are more constrictive. To each their own; it's not a matter of right or wrong.

That said, the call for privacy actually makes sense because, without it, you risk introducing bugs into your code for real. Let us show you what we mean:

```
# oop/private.attrs.py
class A:
    def __init__(self, factor):
        self._factor = factor

    def op1(self):
        print("Op1 with factor {}...".format(self._factor))

class B(A):
    def op2(self, factor):
        self._factor = factor
        print("Op2 with factor {}...".format(self._factor))

obj = B(100)
obj.op1()  # Op1 with factor 100...
obj.op2(42)  # Op2 with factor 42...
obj.op1()  # Op1 with factor 42...  <- This is BAD
```

In the preceding code, we have an attribute called `_factor`, and let us pretend it is so important that it shouldn't be modified at runtime after the instance is created because `op1()` depends on it to function correctly. We've named it with a leading underscore, but the issue here is that the call `obj.op2(42)` modifies it, and this is then reflected in subsequent calls to `op1()`.

We can fix this undesired behavior by adding a second leading underscore:

```
# oop/private.attrs.fixed.py
class A:
    def __init__(self, factor):
        self.__factor = factor

    def op1(self):
        print("Op1 with factor {}...".format(self.__factor))

class B(A):
```

```
    def op2(self, factor):
        self.__factor = factor
        print("Op2 with factor {}...".format(self.__factor))

obj = B(100)
obj.op1()  # Op1 with factor 100...
obj.op2(42)  # Op2 with factor 42...
obj.op1()  # Op1 with factor 100...  <- Now it's good!
```

Now, it is working as desired. Python is kind of magic, and in this case, what is happening is that the name-mangling mechanism has kicked in.

Name mangling means that any attribute name that has at least two leading underscores and at most one trailing underscore, such as `__my_attr`, is replaced with a name that includes an underscore and the class name before the actual name, such as `_ClassName__my_attr`.

This means that when you inherit from a class, the mangling mechanism gives your private attribute two different names in the base and child classes so that name collision is avoided. Every class and instance object stores references to their attributes in a special attribute, called `__dict__`. Let us inspect `obj.__dict__` to see name mangling in action:

```
# oop/private.attrs.py
print(obj.__dict__.keys())
# dict_keys(['_factor'])
```

This is the `_factor` attribute that we find in the problematic version of this example, but look at the one that uses `__factor`:

```
# oop/private.attrs.fixed.py
print(obj.__dict__.keys())
# dict_keys(['_A__factor', '_B__factor'])
```

`obj` has two attributes now, `_A__factor` (mangled within the `A` class) and `_B__factor` (mangled within the `B` class). This is the mechanism that ensures that when you execute `obj.__factor = 42`, `__factor` in `A` isn't changed because you're actually touching `_B__factor`, which has no effect on `_A__factor`.

If you are designing a library with classes that are meant to be used and extended by other developers, you will need to keep this in mind in order to avoid the unintentional overriding of your attributes. Bugs like these can be subtle and hard to spot.

The property decorator

Another thing that would be a crime not to mention is the **property** decorator. Imagine that you have an `age` attribute in a `Person` class and, at some point, you want to make sure that when you change its value, you also check that `age` is within a proper range, such as [18, 99]. You could write accessor methods, such as `get_age()` and `set_age()` (also called **getters** and **setters**), and put the logic there. `get_age()` will most likely just return `age`, while `set_age()` will set its value after checking its validity. The problem is that you may already have some code accessing the `age` attribute directly, which means you're now ready for some refactoring. Languages like Java overcome this problem by using the accessor pattern basically by default. Many Java **Integrated Development Environments (IDEs)** autocomplete an attribute declaration by writing getter and setter accessor method stubs for you on the fly.

But we are not learning Java. Python achieves the same result with the `property` decorator. When you decorate a method with `property`, you can use the name of the method as if it were a data attribute. Because of this, it is always best to refrain from putting logic that would take a while to complete in such methods because, by accessing them as attributes, we do not expect to wait.

Let us look at an example:

```
# oop/property.py
class Person:
    def __init__(self, age):
        self.age = age  # anyone can modify this freely

class PersonWithAccessors:
    def __init__(self, age):
        self._age = age

    def get_age(self):
        return self._age

    def set_age(self, age):
        if 18 <= age <= 99:
            self._age = age
        else:
            raise ValueError("Age must be within [18, 99]")
```

```
class PersonPythonic:
    def __init__(self, age):
        self._age = age

    @property
    def age(self):
        return self._age

    @age.setter
    def age(self, age):
        if 18 <= age <= 99:
            self._age = age
        else:
            raise ValueError("Age must be within [18, 99]")

person = PersonPythonic(39)
print(person.age)  # 39 - Notice we access as data attribute
person.age = 42  # Notice we access as data attribute
print(person.age)  # 42
person.age = 100  # ValueError: Age must be within [18, 99]
```

The `Person` class may be the first version we write. Then, we realize we need to put the range logic in place, so with another language, we would have to rewrite `Person` as the `PersonWithAccessors` class and refactor the code that uses `Person.age`. In Python, we rewrite `Person` as `PersonPythonic` (you normally wouldn't change the name, of course; this is just for the sake of illustration). In `PersonPythonic` the age is stored in a *private* `_age` variable, and we define property getters and setters using the decoration shown, which allows us to keep using the `person` instances as before. A **getter** is a method that is called when we access an attribute for reading. On the other hand, a **setter** is a method that is called when we access an attribute to write it.

Unlike languages that use the getter/setter paradigm, Python allows us to start writing simple code and refactor later, only when we need it; there is no need to pollute the code with accessor methods only because they may be helpful in the future.

The `property` decorator also allows read-only data (by not writing the setter counterpart) and for special actions when the attribute is deleted. Please refer to the official documentation to dig deeper.

The cached_property decorator

One convenient use of properties is when we need to run some code to set up the object we want to use. For example, let us say we needed to connect to a database (or to an API).

In both cases, we might have to set up a client object that knows how to talk to the database (or the API). It is quite common to use a property, in these cases, so that we can hide away the complexity of having to set the client up, and simply use it. Let us show you a simple example:

```
# oop/cached.property.py
class Client:
    def __init__(self):
        print("Setting up the client...")

    def query(self, **kwargs):
        print(f"Performing a query: {kwargs}")

class Manager:
    @property
    def client(self):
        return Client()

    def perform_query(self, **kwargs):
        return self.client.query(**kwargs)
```

In the preceding example, we have a dummy `Client` class, which prints the string `"Setting up the client…"` every time we create a new instance. It also has a pretend `query()` method that prints a string as well. We then have a class, `Manager`, which has a `client` property that creates a new instance of `Client` every time it is called (for example, by a call to `perform_query()`).

If we were to run this code, we would notice that every time we call `perform_query()` on the manager, we see the string `"Setting up the client…"` being printed. When creating a client is expensive, this code would be wasting resources, so it might be better to cache that client, like this:

```
# oop/cached.property.py
class ManualCacheManager:
    @property
    def client(self):
        if not hasattr(self, "_client"):
            self._client = Client()
```

```
        return self._client

    def perform_query(self, **kwargs):
        return self.client.query(**kwargs)
```

The `ManualCacheManager` class is a bit smarter: the `client` property first checks if the attribute `_client` exists on the instance, by calling the built-in `hasattr()` function. If not, it assigns `_client` to a new instance of `Client`. Finally, it simply returns it. Repeatedly accessing the `client` property on this class will only create one instance of `Client`, the first time. From the second call on, `_client` is simply returned with no creation of new instances.

This is such a common need that, in Python 3.8, the `functools` module added the `cached_property` decorator. The beauty of using that, instead of our manual solution, is that if we need to refresh the client, we can simply delete the `client` property, and the next time we call it, it will recreate a brand new `Client` for us. Let us see an example:

```
# oop/cached.property.py
from functools import cached_property

class CachedPropertyManager:
    @cached_property
    def client(self):
        return Client()

    def perform_query(self, **kwargs):
        return self.client.query(**kwargs)

manager = CachedPropertyManager()
manager.perform_query(object_id=42)
manager.perform_query(name_ilike="%Python%")

del manager.client  # This causes a new Client on next call
manager.perform_query(age_gte=18)
```

Running this code gives the following result:

```
$ python cached.property.py
Setting up the client...                        # New Client
Performing a query: {'object_id': 42}           # first query
```

```
Performing a query: {'name_ilike': '%Python%'}   # second query
Setting up the client...                         # Another Client
Performing a query: {'age_gte': 18}              # Third query
```

As you can see, it is only after we manually delete the `manager.client` attribute that we get a new one, when we invoke `manager.perform_query()` again.

Python 3.9 introduced a `cache` decorator, which can be used in conjunction with the `property` decorator, to cover scenarios for which `cached_property` is not suitable. As always, we encourage you to read up on all the details in the official Python documentation and experiment.

Operator overloading

Python's approach to **operator overloading** is brilliant. To overload an operator means giving it a meaning according to the context in which it is used. For example, the + operator means addition when we deal with numbers but concatenation when we deal with sequences.

When using operators, Python calls special methods behind the scenes. For example, the `a[k]` call on a dictionary roughly translates to `type(a).__getitem__(a, k)`. We can override these special methods for our purposes.

As an example, let us create a class that stores a string and evaluates to `True` if `'42'` is part of that string, and `False` otherwise. Also, let us give the class a length property that corresponds to the length of the stored string:

```
# oop/operator.overloading.py
class Weird:
    def __init__(self, s):
        self._s = s

    def __len__(self):
        return len(self._s)

    def __bool__(self):
        return "42" in self._s

weird = Weird("Hello! I am 9 years old!")
print(len(weird))  # 24
print(bool(weird))  # False
```

```
weird2 = Weird("Hello! I am 42 years old!")
print(len(weird2))  # 25
print(bool(weird2))  # True
```

For the complete list of magic methods that you can override to provide your custom implementation of operators for your classes, please refer to the Python data model in the official documentation.

Polymorphism—a brief overview

The word **polymorphism** comes from the Greek *polys* (many, much) and *morphē* (form, shape), and its meaning is the provision of a single interface for entities of different types.

In our car example, we call `engine.start()`, regardless of what kind of engine it is. As long as it exposes the start method, we can call it. That's polymorphism in action.

In other languages, such as Java, in order to give a function the ability to accept different types and call a method on them, those types need to be coded in such a way that they share an interface. In this way, the compiler knows that the method will be available regardless of the type of the object the function is fed (as long as it extends the specific interface, of course).

In Python, things are different. Polymorphism is implicit, and nothing prevents you from calling a method of an object; therefore, technically, there is no need to implement interfaces or other patterns.

There is a special kind of polymorphism called **ad hoc polymorphism**, which is what we saw in the last section on operator overloading. This is the ability of an operator to change shape according to the type of data it is applied to.

Polymorphism also allows Python programmers to simply use the interface (methods and properties) exposed from an object, rather than having to check which class it was instantiated from. This allows the code to be more compact and feel more natural.

We cannot spend too much time on polymorphism, but we encourage you to check it out by yourself; it will expand your understanding of OOP.

Data classes

Before we leave the OOP realm, there is one last thing we want to mention: **data classes**. Introduced in Python 3.7 by PEP 557 (`https://peps.python.org/pep-0557/`), they can be described as *mutable named tuples with defaults*. You can brush up on named tuples in *Chapter 2*, *Built-In Data Types*. Let us dive straight into an example:

```
# oop/dataclass.py
from dataclasses import dataclass

@dataclass
class Body:
    """Class to represent a physical body."""

    name: str
    mass: float = 0.0  # Kg
    speed: float = 1.0  # m/s

    def kinetic_energy(self) -> float:
        return (self.mass * self.speed**2) / 2

body = Body("Ball", 19, 3.1415)
print(body.kinetic_energy())  # 93.755711375 Joule
print(body)  # Body(name='Ball', mass=19, speed=3.1415)
```

In the previous code, we created a class to represent a physical body, with one method that allows us to calculate its kinetic energy (using the formula $E_k=½mv^2$). Notice that `name` is supposed to be a string, while `mass` and `speed` are both floats, and both are given a default value. It is also interesting that we didn't have to write any `__init__()` method; it is done for us by the `dataclass` decorator, along with methods for comparison and to produce the string representation of the object (implicitly called on the last line by `print`).

Another thing to notice is how `name`, `mass`, and `speed` are defined. This technique is called **type hinting** and will be the subject of *Chapter 12*, *Introduction to Type Hinting*.

You can read all the specifications in PEP 557 if you are curious, but for now, just remember that data classes might offer a nicer, slightly more powerful alternative to named tuples, if you need it.

Writing a custom iterator

Now, we have all the tools to appreciate how we can write our own custom iterator. Let us first define what iterable and iterator mean:

- **Iterable**: An object is said to be iterable if it can return its members one at a time. Lists, tuples, strings, and dictionaries are all iterables. Custom objects that define either of the `__iter__()` or `__getitem__()` methods are also iterables.
- **Iterator**: An object is said to be an iterator if it represents a stream of data. A custom iterator is required to provide an implementation for the `__iter__()` method that returns the object itself, as well as an implementation for the `__next__()` method that returns the next item of the data stream until the stream is exhausted, at which point all successive calls to `__next__()` simply raise a `StopIteration` exception. Built-in functions, such as `iter()` and `next()`, are mapped to call the `__iter__()` and `__next__()` methods on an object, behind the scenes.

Exceptions will be the subject of *Chapter 7, Exceptions and Context Managers*. They can represent errors during code execution but are also used to regulate the flow of execution, and Python relies on them for mechanisms such as the iteration protocol.

Let us write an iterator that returns all the odd characters from a string first, and then the even ones:

```
# iterators/iterator.py
class OddEven:
    def __init__(self, data):
        self._data = data
        self.indexes = list(range(0, len(data), 2)) + list(
            range(1, len(data), 2)
        )

    def __iter__(self):
        return self

    def __next__(self):
        if self.indexes:
            return self._data[self.indexes.pop(0)]
        raise StopIteration

oddeven = OddEven("0123456789")
print("".join(c for c in oddeven))  # 0246813579

oddeven = OddEven("ABCD")  # or manually...
```

```
it = iter(oddeven)  # this calls oddeven.__iter__ internally
print(next(it))  # A
print(next(it))  # C
print(next(it))  # B
print(next(it))  # D
```

So, we provide an implementation for `__iter__()` that returns the object itself, and one for `__next__()`. Let us go through it. What needs to happen is the return of `_data[0]`, `_data[2]`, `_data[4]`, `...`, `_data[1]`, `_data[3]`, `_data[5]`, and so on until we have returned every item in the data. To do that, we prepare a list of indexes, such as [0, 2, 4, 6, ..., 1, 3, 5, ...], and while there is at least one element in the list, we pop the first one out and return the corresponding element from the data list, thereby achieving our goal. When `indexes` is empty, we raise `StopIteration`, as required by the iterator protocol.

There are other ways to achieve the same result, so go ahead and try to code a different one yourself. Make sure that the end result works for all edge cases, empty sequences, and sequences of lengths of 1, 2, and so on.

Summary

In this chapter, we looked at decorators, discovered their purpose, and covered a few examples, using one or more at the same time. We also saw decorators that take arguments, which are usually used as decorator factories.

We have scratched the surface of OOP in Python. We covered all the basics, so you should now be able to understand the code that will come in future chapters. We talked about all kinds of methods and attributes that you can write in a class; we explored inheritance versus composition, method overriding, properties, operator overloading, and polymorphism.

Finally, we very briefly touched on iterators, which should enrich your understanding of generators.

In the next chapter, we are going to learn about exceptions and context managers.

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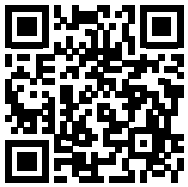

7

Exceptions and Context Managers

> *The best-laid schemes o' mice an' men Gang aft agley.*
>
> *– Robert Burns*

This famous line by Robert Burns should be etched into the mind of every programmer. Even if our code is correct, errors will happen. If we do not deal with them properly, they can cause our best-laid schemes to go awry.

Unhandled errors can cause software to crash or misbehave. Depending on the nature of the software in question, this could have serious consequences. Therefore, it is important to learn how to detect and handle errors. We encourage you to cultivate the habit of always thinking about what errors can occur and how your code should respond when they do.

This chapter is all about errors and dealing with the unexpected. We will be learning about **exceptions**, which are Python's way of signaling that an error or other exceptional event has occurred. We will also talk about **context managers**, which provide a mechanism to encapsulate and reuse error-handling code.

In this chapter, we are going to cover the following:

- Exceptions
- Context managers

Exceptions

Even though we have not covered the topic yet, we expect that by now you have at least a vague idea of what an exception is. In the previous chapters, we saw that when an iterator is exhausted, calling `next()` on it raises a `StopIteration` exception. We got an `IndexError` when we tried accessing a list at a position that was outside the valid range. We also encountered `AttributeError` when we tried accessing an attribute that did not exist on an object, and `KeyError` when we tried to access a nonexistent key in a dictionary. In this chapter, we will discuss exceptions in more depth.

Even when an operation or a piece of code is correct, there are often conditions in which something may go wrong. For example, if we are converting user input from `str` to `int`, the user could have accidentally typed a letter in place of a digit, making it impossible for us to convert that value into a number. When dividing numbers, we may not know in advance whether we might attempt a division by 0. When opening a file, it could be missing or corrupted.

When an error is detected during execution, it is called an **exception**. Exceptions are not necessarily lethal; in fact, the `StopIteration` exception is deeply integrated into the Python generator and iterator mechanisms. Normally, however, if you do not take the necessary precautions, an exception will cause your application to break. Sometimes, this is the desired behavior, but in other cases, we want to prevent and control problems such as these. For example, if a user tries to open a corrupted file, we can alert them to the problem and give them an opportunity to fix it. Let us see an example of a few exceptions:

```
# exceptions/first.example.txt
>>> gen = (n for n in range(2))
>>> next(gen)
0
>>> next(gen)
1
>>> next(gen)
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
StopIteration
>>> print(undefined_name)
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
```

```
NameError: name 'undefined_name' is not defined
>>> mylist = [1, 2, 3]
>>> mylist[5]
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
IndexError: list index out of range
>>> mydict = {"a": "A", "b": "B"}
>>> mydict["c"]
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
KeyError: 'c'
>>> 1 / 0
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
ZeroDivisionError: division by zero
```

As you can see, the Python shell is quite forgiving. We can see `Traceback` so that we have information about the error, but the shell itself still runs normally. This is a special behavior; a regular program or a script would normally exit immediately if nothing were done to handle exceptions. Let us see a quick example:

```
# exceptions/unhandled.py
1 + "one"
print("This line will never be reached")
```

If we run this code, we get the following output:

```
$ python exceptions/unhandled.py
Traceback (most recent call last):
  File "exceptions/unhandled.py", line 2, in <module>
    1 + "one"
    ~~^~~~~~
TypeError: unsupported operand type(s) for +: 'int' and 'str'
```

Because we did nothing to handle the exception, Python immediately exits once an exception occurs (after printing out information about the error).

Raising exceptions

The exceptions we have seen so far were raised by the Python interpreter when it detected an error. However, you can also raise exceptions yourself, when a situation occurs that your own code considers to be an error. To raise an exception, use the `raise` statement. Here is an example:

```
# exceptions/raising.txt
>>> raise NotImplementedError("I'm afraid I can't do that")
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
NotImplementedError: I'm afraid I can't do that
```

There are no restrictions on which exception types you can raise. This allows you to choose the exception type that best describes the error condition that has occurred. You can also define your own exception types (we will see how to do that in a moment). Notice that the argument we passed to the `Exception` class is printed out as part of the error message.

Python has too many built-in exceptions to list here, but they are all documented at `https://docs.python.org/3.12/library/exceptions.html#bltin-exceptions`.

Defining your own exceptions

As we mentioned in the previous section, you can define your own custom exceptions. In fact, it is pretty common for libraries, for example, to define their own exceptions.

All you need to do is define a class that inherits from any other exception class. All exceptions derive from `BaseException`; however, this class is not intended to be directly subclassed. Your custom exceptions should inherit from `Exception` instead. In fact, nearly all built-in exceptions also inherit from `Exception`. Exceptions that do not inherit from `Exception` are meant for internal use by the Python interpreter.

Tracebacks

The **traceback** that Python prints when an unhandled exception occurs may initially look intimidating, but it is quite useful for understanding what happened to cause the exception. For this example, we are using a mathematical formula to solve quadratic equations; it is not important if you are not familiar with it, as you do not need to understand it. Let us look at a traceback and see what it can tell us:

```
# exceptions/trace.back.py
def squareroot(number):
    if number < 0:
        raise ValueError("No negative numbers please")
    return number**.5

def quadratic(a, b, c):
    d = b**2 - 4 * a * c
    return (
        (-b - squareroot(d)) / (2 * a),
        (-b + squareroot(d)) / (2 * a)
    )

quadratic(1, 0, 1)  # x**2 + 1 == 0
```

Here, we defined a function called `quadratic()`, which uses the famous quadratic formula to find the solution of a quadratic equation. Instead of using the `sqrt()` function from the `math` module, we wrote our own version (`squareroot()`), which raises an exception if the number is negative. When we call `quadratic(1, 0, 1)` to solve the equation $x^2+1=0$, we will get a `ValueError` because `d` is negative. When we run this, we get the following:

```
$ python exceptions/trace.back.py
Traceback (most recent call last):
  File "exceptions/trace.back.py", line 16, in <module>
    quadratic(1, 0, 1)  # x**2 + 1 == 0
    ^^^^^^^^^^^^^^^^^
  File "exceptions/trace.back.py", line 11, in quadratic
    (-b - squareroot(d)) / (2 * a),
          ^^^^^^^^^^^^
  File "exceptions/trace.back.py", line 4, in squareroot
    raise ValueError("No negative numbers please")
ValueError: No negative numbers please
```

It is often useful to read tracebacks from bottom to top. On the very last line, we have the error message, telling us what went wrong: `ValueError: No negative numbers please`. The preceding lines tell us where the exception was raised (line 4 of `exceptions/trace.back.py` in the `squareroot()` function).

We can also see the sequence of function calls that got us to the point where the exception was raised: `squareroot()` was called on line 11 by the function `quadratic()`, which was called on line 16, at the top level of the module. As you can see, the traceback is like a map that shows us the path through the code to where the exception happened. Following that path and examining the code in each function along the way is often helpful when you want to understand why an exception happened.

There have been several improvements to error messages in Python 3.10, 3.11, and 3.12. For example, the ^^^^ characters underlining the exact part of each statement or expression in the traceback that led to the exception were added in Python 3.11.

Handling exceptions

To handle an exception in Python, you use the `try` statement. When you enter the `try` clause, Python will watch out for one or more different types of exceptions (according to how you instruct it), and if they are raised, it allows you to react.

The `try` statement is composed of the `try` clause, which opens the statement, followed by one or more `except` clauses that define what to do when an exception is caught. The `except` clauses may optionally be followed by an `else` clause, which is executed when the `try` clause is exited without any exception raised. After the `except` and `else` clauses, we can have a `finally` clause (also optional), whose code is executed regardless of whatever happened in the other clauses. The `finally` clause is typically used to clean up resources. You are also allowed to omit the `except` and `else` clauses and only have a `try` clause followed by a `finally` clause. This is helpful if we want exceptions to be propagated and handled elsewhere, but we do have some cleanup code that must be executed regardless of whether an exception occurs.

The order of the clauses is important. It must be `try`, `except`, `else`, then `finally`. Also, remember that `try` must be followed by at least one `except` clause or a `finally` clause. Let us see an example:

```
# exceptions/try.syntax.py
def try_syntax(numerator, denominator):
    try:
        print(f"In the try block: {numerator}/{denominator}")
        result = numerator / denominator
    except ZeroDivisionError as zde:
        print(zde)
    else:
```

```
        print("The result is:", result)
        return result
    finally:
        print("Exiting")

print(try_syntax(12, 4))
print(try_syntax(11, 0))
```

This example defines a simple `try_syntax()` function. We perform the division of two numbers. We are prepared to catch a `ZeroDivisionError` exception, which will occur if we call the function with `denominator = 0`. Initially, the code enters the `try` block. If `denominator` is not `0`, `result` is calculated and, after leaving the `try` block, execution resumes in the `else` block. We print `result` and return it. Take a look at the output, and you'll notice that just before returning `result`, which is the exit point of the function, Python executes the `finally` clause.

When `denominator` is `0`, things change. Our attempt to calculate `numerator / denominator` raises a `ZeroDivisionError`. As a result, we enter the `except` block and print `zde`.

The `else` block is not executed because an exception was raised in the `try` block. Before (implicitly) returning `None`, we still execute the `finally` block. Look at the output and see whether it makes sense to you:

```
$ python exceptions/try.syntax.py
In the try block: 12/4
The result is: 3.0
Exiting
3.0
In the try block: 11/0
division by zero
Exiting
None
```

When you execute a `try` block, you may want to catch more than one exception. For example, when calling the `divmod()` function, you can get a `ZeroDivisionError` if the second argument is `0`, or `TypeError` if either argument is not a number. If you want to handle both in the same way, you can structure your code like this:

```
# exceptions/multiple.py
values = (1, 2)
try:
```

```
    q, r = divmod(*values)
except (ZeroDivisionError, TypeError) as e:
    print(type(e), e)
```

This code will catch both `ZeroDivisionError` and `TypeError`. Try changing `values = (1, 2)` to `values = (1, 0)` or `values = ('one', 2)`, and you will see the output change.

If you need to handle different exception types differently, you can use multiple `except` clauses, like this:

```
# exceptions/multiple.py
try:
    q, r = divmod(*values)
except ZeroDivisionError:
    print("You tried to divide by zero!")
except TypeError as e:
    print(e)
```

Keep in mind that an exception is handled in the first block that matches that exception class or any of its base classes. Therefore, when you stack multiple `except` clauses like we have done here, make sure that you put specific exceptions at the top and generic ones at the bottom. In OOP terms, derived classes should be placed before their base classes. Moreover, remember that only one `except` handler is executed when an exception is raised.

Python also allows you to use an `except` clause without specifying any exception type (this is equivalent to writing `except BaseException`). You should, however, avoid doing this as it means you will also capture exceptions that are intended for internal use by the interpreter. They include the so-called *system-exiting exceptions*. These are `SystemExit`, which is raised when the interpreter exits via a call to the `exit()` function, and `KeyboardInterrupt`, which is raised when the user terminates the application by pressing *Ctrl + C* (or *Delete* on some systems).

You can also raise exceptions from within an `except` clause. For example, you might want to replace a built-in exception (or one from a third-party library) with your own custom exception. This is quite a common technique when writing libraries, as it helps shield users from the implementation details of the library. Let us see an example:

```
# exceptions/replace.txt
>>> class NotFoundError(Exception):
```

```
...     pass
...
>>> vowels = {"a": 1, "e": 5, "i": 9, "o": 15, "u": 21}
>>> try:
...     pos = vowels["y"]
... except KeyError as e:
...     raise NotFoundError(*e.args)
...
Traceback (most recent call last):
  File "<stdin>", line 2, in <module>
KeyError: 'y'
During handling of the above exception, another exception occurred:
Traceback (most recent call last):
  File "<stdin>", line 4, in <module>
NotFoundError: y
```

By default, Python assumes that an exception that happens within an `except` clause is an unexpected error and helpfully prints out tracebacks for both exceptions. We can tell the interpreter that we are deliberately raising the new exception by using a `raise from` statement:

```
# exceptions/replace.py
>>> try:
...     pos = vowels["y"]
... except KeyError as e:
...     raise NotFoundError(*e.args) from e
...
Traceback (most recent call last):
  File "<stdin>", line 2, in <module>
KeyError: 'y'
The above exception was the direct cause of the following exception:
Traceback (most recent call last):
  File "<stdin>", line 4, in <module>
NotFoundError: y
```

The error message has changed, but we still get both tracebacks, which is very handy for debugging. If you really wanted to completely suppress the original exception, you could use `from None` instead of `from e` (try this yourself).

You can also use `raise` by itself, without specifying a new exception, to re-raise the original exception. This is sometimes useful if you want to log the fact that an exception has occurred without suppressing or replacing the exception.

Since Python 3.11, it is also possible to add notes to exceptions. This allows you to add extra information to be displayed as part of the traceback without suppressing or replacing the original exception. To see how this works, we will modify the quadratic formula example from earlier in the chapter, and add a note to the exception:

```
# exceptions/note.py
def squareroot(number):
    if number < 0:
        raise ValueError("No negative numbers please")
    return number**0.5


def quadratic(a, b, c):
    d = b**2 - 4 * a * c
    try:
        return (
            (-b - squareroot(d)) / (2 * a),
            (-b + squareroot(d)) / (2 * a),
        )
    except ValueError as e:
        e.add_note(f"Cannot solve {a}x**2 + {b}x + {c} == 0")
        raise

quadratic(1, 0, 1)
```

We have highlighted the lines where we added a note and re-raised the exception. The output when we run this looks as follows:

```
$ python exceptions/note.py
Traceback (most recent call last):
  File "exceptions/note.py", line 20, in <module>
    quadratic(1, 0, 1)
  File "exceptions/note.py", line 12, in quadratic
    (-b - squareroot(d)) / (2 * a),
```

```
          ^^^^^^^^^^^^
  File "exceptions/note.py", line 4, in squareroot
    raise ValueError("No negative numbers please")
ValueError: No negative numbers please
Cannot solve 1x**2 + 0x + 1 == 0
```

The note has been printed below the original error message. You can add as many notes as you need, by calling `add_note()` multiple times. The notes must all be strings.

Programming with exceptions can be tricky. You could inadvertently hide bugs by trapping exceptions that would have alerted you to their presence. Play it safe by keeping these simple guidelines in mind:

- Keep the `try` clause as short as possible. It should contain only the code that may cause the exception(s) that you want to handle.
- Make the `except` clauses as specific as you can. It may be tempting to just write `except Exception`, but if you do, you will almost certainly end up catching exceptions you did not actually intend to catch.
- Use tests to ensure that your code handles both expected and unexpected errors correctly. We shall talk more about writing tests in *Chapter 10, Testing*.

If you follow these suggestions, you will minimize the chance of getting it wrong.

Exception groups

When working with large collections of data, it can be inconvenient to immediately stop and raise an exception when an error occurs. It is often better to process all the data and report on all errors that occurred at the end. This allows the user to deal with all the errors at once, rather than having to rerun the process multiple times, fixing errors one by one.

One way of achieving this is to build up a list of errors and return it. However, this has the disadvantage that you cannot use a `try`/`except` statement to handle the errors. Some libraries have worked around this by creating a container exception class and wrapping the collected errors in an instance of this class. This allows you to handle the container exception in an `except` clause and inspect it to access the nested exceptions.

Since Python 3.11, there is a new built-in exception class, `ExceptionGroup`, that was specifically designed as such a container exception. Having this feature built into the language has the advantage that the traceback also shows the tracebacks of each of the nested exceptions.

For example, suppose we need to validate a list of ages to ensure that the values are all positive integers. We could write something like the following:

```
# exceptions/groups/util.py

def validate_age(age):
    if not isinstance(age, int):
        raise TypeError(f"Not an integer: {age}")
    if age < 0:
        raise ValueError(f"Negative age: {age}")

def validate_ages(ages):
    errors = []
    for age in ages:
        try:
            validate_age(age)
        except Exception as e:
            errors.append(e)

    if errors:
        raise ExceptionGroup("Validation errors", errors)
```

The `validate_ages()` function calls `validate_age()` for each element of `ages`. It catches any exceptions that occur and appends them to the `errors` list. If the list of errors is not empty after the loops complete, we raise `ExceptionGroup`, passing in the error message `"Validation errors"` and the list of errors that occurred.

If we call this from a Python console with a list containing some invalid ages, we get the following traceback:

```
# exceptions/groups/exc.group.txt
>>> from util import validate_ages
>>> validate_ages([24, -5, "ninety", 30, None])
  + Exception Group Traceback (most recent call last):
  |   File "<stdin>", line 1, in <module>
  |   File "exceptions/groups/util.py", line 20, in validate_ages
  |     raise ExceptionGroup("Validation errors", errors)
  | ExceptionGroup: Validation errors (3 sub-exceptions)
  +-+---------------- 1 ----------------
```

```
    | Traceback (most recent call last):
    |   File "exceptions/groups/util.py", line 15, in validate_ages
    |     validate_age(age)
    |   File "exceptions/groups/util.py", line 8, in validate_age
    |     raise ValueError(f"Negative age: {age}")
    | ValueError: Negative age: -5
    +---------------- 2 ----------------
    | Traceback (most recent call last):
    |   File "exceptions/groups/util.py", line 15, in validate_ages
    |     validate_age(age)
    |   File "exceptions/groups/util.py", line 6, in validate_age
    |     raise TypeError(f"Not an integer: {age}")
    | TypeError: Not an integer: ninety
    +---------------- 3 ----------------
    | Traceback (most recent call last):
    |   File "exceptions/groups/util.py", line 15, in validate_ages
    |     validate_age(age)
    |   File "exceptions/groups/util.py", line 6, in validate_age
    |     raise TypeError(f"Not an integer: {age}")
    | TypeError: Not an integer: None
    +------------------------------------
```

Note that we get the traceback for the `ExceptionGroup`, including the error message we specified when raising it (`"Validation errors"`) and an indication that the group contains three sub-exceptions. Indented below this, we get the traceback for each of the nested sub-exceptions. To aid readability, the sub-exception tracebacks are numbered and separated by dashed lines.

We can handle `ExceptionGroup` exceptions just like any other type of exception:

```
# exceptions/groups/handle.group.txt
>>> from util import validate_ages
>>> try:
...     validate_ages([24, -5, "ninety", 30, None])
... except ExceptionGroup as e:
...     print(e)
...     print(e.exceptions)
...
Validation errors (3 sub-exceptions)
(ValueError('Negative age: -5'),
```

```
 TypeError('Not an integer: ninety'),
 TypeError('Not an integer: None'))
```

Note that we can access the nested list of sub-exceptions via the (read-only) `exceptions` property.

PEP 654 (`https://peps.python.org/pep-0654/`), which introduced `ExceptionGroup` to the language, also introduced a new variant of the `try`/`except` statement that allows us to handle nested sub-exceptions of particular types within an `ExceptionGroup`. This new syntax uses the keyword `except*` instead of `except`. In our validation example, this allows us to have separate handling for invalid types and invalid values without having to manually iterate and filter the exceptions:

```
# exceptions/groups/handle.nested.txt
>>> from util import validate_ages
>>> try:
...     validate_ages([24, -5, "ninety", 30, None])
... except* TypeError as e:
...     print("Invalid types")
...     print(type(e), e)
...     print(e.exceptions)
... except* ValueError as e:
...     print("Invalid values")
...     print(type(e), e)
...     print(e.exceptions)
...
Invalid types
<class 'ExceptionGroup'> Validation errors (2 sub-exceptions)
(TypeError('Not an integer: ninety'),
 TypeError('Not an integer: None'))
Invalid values
<class 'ExceptionGroup'> Validation errors (1 sub-exception)
(ValueError('Negative age: -5'),)
```

The call to `validate_ages()` raises an exception group containing three exceptions: two instances of `TypeError` and a `ValueError`. The interpreter matches each `except*` clause to the nested exceptions. The first clause matches, so the interpreter creates a new `ExceptionGroup` containing all the `TypeError` instances from the original group and assigns this to `e` within the body of this clause. We print the string `"Invalid types"`, followed by the type and value of `e` and then `e.exceptions`. The remaining exceptions are then matched against the next `except*` clause.

This time, all the `ValueError` instances match, so `e` is assigned to a new `ExceptionGroup` containing these. We print the string `"Invalid values"`, again followed by `type(e)`, `e`, and `e.exceptions`. At this point, there are no unhandled exceptions left in the group, so execution resumes normally.

It is important to be aware that this behavior is different from a normal `try/except` statement. In a normal `try/except` statement, only one `except` clause is executed: the first that matches the raised exception. In a `try/except*` statement, each matching `except*` clause is executed until there are no unhandled exceptions remaining in the group. If any unhandled exceptions remain after all the `except*` clauses have been processed, they will be reraised at the end as a new `ExceptionGroup`:

```
# exceptions/groups/handle.nested.txt
>>> try:
...     validate_ages([24, -5, "ninety", 30, None])
... except* ValueError as e:
...     print("Invalid values")
...
Invalid values
  + Exception Group Traceback (most recent call last):
  |   File "<stdin>", line 2, in <module>
  |   File "exceptions/groups/util.py", line 20, in validate_ages
  |     raise ExceptionGroup("Validation errors", errors)
  | ExceptionGroup: Validation errors (2 sub-exceptions)
  +-+---------------- 1 ----------------
    | Traceback (most recent call last):
    |   File "exceptions/groups/util.py", line 15, in validate_ages
    |     validate_age(age)
    |   File "exceptions/groups/util.py", line 6, in validate_age
    |     raise TypeError(f"Not an integer: {age}")
    | TypeError: Not an integer: ninety
    +---------------- 2 ----------------
    | Traceback (most recent call last):
    |   File "exceptions/groups/util.py", line 15, in validate_ages
    |     validate_age(age)
    |   File "exceptions/groups/util.py", line 6, in validate_age
    |     raise TypeError(f"Not an integer: {age}")
    | TypeError: Not an integer: None
    +------------------------------------
```

Another important point to note is that if an exception is raised within a `try/except*` statement that is not an `ExceptionGroup` instance, its type will be matched against the `except*` clauses. If a match is found, the exception will be wrapped in an `ExceptionGroup` before being passed to the `except*` body:

```
# exceptions/groups/handle.nested.txt
>>> try:
...     raise RuntimeError("Ungrouped")
... except* RuntimeError as e:
...     print(type(e), e)
...     print(e.exceptions)
...
<class 'ExceptionGroup'>  (1 sub-exception)
(RuntimeError('Ungrouped'),)
```

This means that it is always safe to assume that the exception being handled within an `except*` clause is an `ExceptionGroup` instance.

Not only for errors

Before we move on to talk about context managers, we want to show you a different use of exceptions. In this example, we will demonstrate that exceptions can be used for more than just errors:

```
# exceptions/for.loop.py
n = 100
found = False
for a in range(n):
    if found:
        break
    for b in range(n):
        if found:
            break
        for c in range(n):
            if 42 * a + 17 * b + c == 5096:
                found = True
                print(a, b, c)  # 79 99 95
                break
```

In the code above, we use three nested loops to find a combination of three integers (`a`, `b`, and `c`) that satisfy a particular equation. At the start of each of the outer loops, we check the value of a flag (`found`), which is set to `True` when we find a solution to the equation. This allows us to break out of all three loops as quickly as possible when we have a solution. We find the logic to check the flag rather inelegant, as it obscures the rest of the code, so we came up with an alternative approach:

```
# exceptions/for.loop.py
class ExitLoopException(Exception):
    pass

try:
    n = 100
    for a in range(n):
        for b in range(n):
            for c in range(n):
                if 42 * a + 17 * b + c == 5096:
                    raise ExitLoopException(a, b, c)
except ExitLoopException as ele:
    print(ele.args)  # (79, 99, 95)
```

Hopefully, you can appreciate how much more elegant this is. Now the breakout logic is entirely handled with a simple exception whose name even hints at its purpose. As soon as the result is found, we raise `ExitLoopException` with the values that satisfy our condition, and immediately the control is given to the `except` clause that handles it. Notice that we can use the `args` attribute of the exception to get the values that were passed to the constructor.

Now we should have a good understanding of what exceptions are, and how they are used to manage errors, flow, and exceptional situations. We are ready to move on to the next topic: **context managers**.

Context managers

When working with external resources, we usually need to perform some cleanup steps when we are done. For example, after writing data to a file, we then need to close the file. Failing to clean up properly could result in all manner of bugs. Therefore, we must ensure that our cleanup code will be executed even if an exception happens. We could use `try/finally` statements, but this is not always convenient and could result in a lot of repetition, as we often have to perform similar cleanup steps whenever we work with a particular type of resource. **Context managers** solve this problem by creating an execution context in which we can work with a resource and automatically perform any necessary cleanup when we leave that context, even if an exception was raised.

Another use case of context managers is to make temporary changes to the global state of our program. One example of a global state that we may want to modify temporarily is the precision for decimal computations. For example, in data science applications, we sometimes need to perform a particular computation to a specific precision, but we want to retain the default precision for the rest of our computations. We could achieve this by doing something like the following:

```
# context/decimal.prec.py
from decimal import Context, Decimal, getcontext, setcontext

one = Decimal("1")
three = Decimal("3")

orig_ctx = getcontext()
ctx = Context(prec=5)
setcontext(ctx)
print(f"{ctx}\n")
print("Custom decimal context:", one / three)
setcontext(orig_ctx)
print("Original context restored:", one / three)
```

Notice that we store the current context, set a new context (with a modified precision), perform our calculation, and finally restore the original context.

You may recall that the `Decimal` class allows us to perform arbitrary precision computations with decimal numbers. If not, you may want to review the relevant section of *Chapter 2*, *Built-In Data Types*, now.

Running this produces the following output:

```
$ python context/decimal.prec.py
Context(prec=5, rounding=ROUND_HALF_EVEN, Emin=-999999,
        Emax=999999, capitals=1, clamp=0, flags=[],
        traps=[InvalidOperation, DivisionByZero, Overflow])

Custom decimal context: 0.33333
Original context restored: 0.33333333333333333333333333333
```

In the above example, we have printed the `context` object to show you what it contains. The rest of the code seems fine, but if an exception happened before we could restore the original context, the results of all subsequent computations would be incorrect. We can fix this by using a `try/finally` statement:

```
# context/decimal.prec.try.py
from decimal import Context, Decimal, getcontext, setcontext

one = Decimal("1")
three = Decimal("3")

orig_ctx = getcontext()
ctx = Context(prec=5)
setcontext(ctx)
try:
    print("Custom decimal context:", one / three)
finally:
    setcontext(orig_ctx)
print("Original context restored:", one / three)
```

That is much safer. Even if an exception does happen in that `try` block, we will always restore the original context. It is not very convenient to have to save the context and then restore it in a `try/finally` statement every time we need to work with a modified precision, though. Doing so would also violate the **DRY** principle. We can avoid that by using the `localcontext` context manager from the `decimal` module. This context manager will set and restore the context for us:

```
# context/decimal.prec.ctx.py
from decimal import Context, Decimal, localcontext

one = Decimal("1")
three = Decimal("3")

with localcontext(Context(prec=5)) as ctx:
    print("Custom decimal context:", one / three)
print("Original context restored:", one / three)
```

The `with` statement is used to enter a runtime context defined by the `localcontext` context manager. When exiting the code block delimited by the `with` statement, any cleanup operation defined by the context manager (in this case, restoring the decimal context) is executed automatically.

It is also possible to combine multiple context managers in one `with` statement. This is quite useful for situations where you need to work with multiple resources at the same time:

```
# context/multiple.py
from decimal import Context, Decimal, localcontext

one = Decimal("1")
three = Decimal("3")

with (
    localcontext(Context(prec=5)),
    open("output.txt", "w") as out_file
):
    out_file.write(f"{one} / {three} = {one / three}\n")
```

Here, we enter a local context and open a file (which acts as a context manager) in one `with` statement. We perform a calculation and write the result to the file. When we exit the `with` block, the file is automatically closed, and the default decimal context is restored. Do not worry too much about the details of working with files for now; we will discuss that in detail in *Chapter 8*, *Files and Data Persistence*.

Before Python 3.10, surrounding multiple context managers in parentheses, as we did here, would have resulted in a `SyntaxError`. In older versions of Python, we would have had to fit both context managers into a single line of code or put the line break inside the parentheses of the `localcontext()` or `open()` calls.

Apart from decimal contexts and files, many other objects in the Python standard library can be used as context managers. Here are some examples:

- Socket objects, which implement a low-level networking interface, can be used as context managers to automatically close network connections.
- The lock classes used for synchronization in concurrent programming use the context manager protocol to automatically release locks.

In the rest of this chapter, we will show you how you can implement your own context managers.

Class-based context managers

Context managers work via two magic methods: `__enter__()` is called just before entering the body of the `with` statement and `__exit__()` is called when exiting the `with` statement body. This means that you can create your own context manager simply by writing a class that implements these methods:

```
# context/manager.class.py
class MyContextManager:
    def __init__(self):
        print("MyContextManager init", id(self))
    def __enter__(self):
        print("Entering 'with' context")
        return self
    def __exit__(self, exc_type, exc_val, exc_tb):
        print(f"{exc_type=} {exc_val=} {exc_tb=}")
        print("Exiting 'with' context")
        return True
```

Here, we have defined a context manager class called `MyContextManager`. There are a few interesting things to note about this class. Notice that the `__enter__()` method returns `self`. This is quite common, but by no means required; you can return whatever you want from `__enter__()`, even `None`. The return value of the `__enter__()` method will be assigned to the variable named in the `as` clause of the `with` statement. Also, notice the `exc_type`, `exc_val`, and `exc_tb` parameters of the `__exit__()` function. If an exception is raised within the body of the `with` statement, the interpreter will pass the *type*, *value*, and *traceback* of the exception as arguments through these parameters. If no exception is raised, all three arguments will be `None`.

Also, notice that the `__exit__()` method returns `True`. This will cause any exception raised within the `with` statement body to be suppressed (as if we had handled it in a `try/except` statement). If we had returned `False` instead, such an exception would continue to be propagated after our `__exit__()` method has executed. The ability to suppress exceptions means that a context manager can be used as an exception handler. The benefit of this is that we can write our exception-handling logic once and reuse it wherever we need it.

Let us see our context manager in action:

```
# context/manager.class.py
ctx_mgr = MyContextManager()
print("About to enter 'with' context")
```

```
with ctx_mgr as mgr:
    print("Inside 'with' context")
    print(id(mgr))
    raise Exception("Exception inside 'with' context")
    print("This line will never be reached")
print("After 'with' context")
```

Here, we have instantiated our context manager in a separate statement, before the `with` statement. We did this to make it easier for you to see what is happening. However, it is much more common for those steps to be combined, like `with MyContextManager() as mgr`. Running this code produces the following output:

```
$ python context/manager.class.py
MyContextManager init 140340228792272
About to enter 'with' context
Entering 'with' context
Inside 'with' context
140340228792272
exc_type=<class 'Exception'> exc_val=Exception("Exception inside
'with' context") exc_tb=<traceback object at 0x7fa3817c5340>
Exiting 'with' context
After 'with' context
```

Study this output carefully to make sure you understand what is happening. We have printed some IDs to help verify that the object assigned to `mgr` is really the same object that we returned from `__enter__()`. Try changing the return values from the `__enter__()` and `__exit__()` methods and see what effect that has.

Generator-based context managers

If you are implementing a class that represents some resource that needs to be acquired and released, it makes sense to implement that class as a context manager. Sometimes, however, we want to implement context manager behavior, but we do not have a class that it makes sense to attach that behavior to. For example, we may just want to use a context manager to reuse some error-handling logic. In such situations, it would be rather tedious to have to write an additional class purely to implement the desired context manager behavior.

The `contextmanager` decorator from the `contextlib` module is useful for situations like this. It takes a *generator function* and converts it into a context manager (if you do not remember how generator functions work, you should review *Chapter 5*, *Comprehensions and Generators*). The decorator wraps the generator in a context manager object. The `__enter__()` method of this object starts the generator and returns whatever the generator yields. If an exception occurs within the `with` statement body, the `__exit__()` method passes the exception into the generator (using the generator's `throw` method). Otherwise, `__exit__()` simply calls `next` on the generator. Note that the generator must only yield once; a `RuntimeError` will be raised if the generator yields a second time. Let us convert our previous example into a generator-based context manager:

```
# context/generator.py
from contextlib import contextmanager

@contextmanager
def my_context_manager():
    print("Entering 'with' context")
    val = object()
    print(id(val))
    try:
        yield val
    except Exception as e:
        print(f"{type(e)=} {e=} {e.__traceback__=}")
    finally:
        print("Exiting 'with' context")

print("About to enter 'with' context")
with my_context_manager() as val:
    print("Inside 'with' context")
    print(id(val))
    raise Exception("Exception inside 'with' context")
    print("This line will never be reached")
print("After 'with' context")
```

The output from running this is similar to the previous example:

```
$ python context/generator.py
About to enter 'with' context
Entering 'with' context
```

```
139768531985040
Inside 'with' context
139768531985040
type(e)=<class 'Exception'> e=Exception("Exception inside 'with'
context") e.__traceback__=<traceback object at 0x7f1e65a42800>
Exiting 'with' context
After 'with' context
```

Most context manager generators have a similar structure to `my_context_manager()` in this example. They have some setup code, followed by a `yield` inside a `try` statement. Here, we yielded an arbitrary object so that you can see that the same object is made available via the `as` clause of the `with` statement. It is also common to have just a bare `yield` with no value (in which case, `None` is yielded). This is equivalent to returning `None` from the `__enter__()` method of a context manager class. In such cases, the `as` clause of the `with` statement will typically be omitted.

Another useful feature of generator-based context managers is that they can also be used as function decorators. This means that if the entire body of a function needs to be inside a `with` statement context, you could save a level of indentation and just decorate the function instead.

In addition to the `contextmanager` decorator, the `contextlib` module also contains many useful context managers. The documentation also provides several helpful examples of using and implementing context managers. Make sure you read it at `https://docs.python.org/3/library/contextlib.html`.

The examples we gave in this section do not do anything useful. They were created purely to show you how context managers work. Study these examples carefully until you are confident that you understand them completely. Then start writing your own context managers (both as classes and generators). Try to convert the `try/except` statement for breaking out of a nested loop that we saw earlier in this chapter into a context manager. The `measure` decorator that we wrote in *Chapter 6*, *OOP, Decorators, and Iterators*, is also a good candidate for converting to a context manager.

Summary

In this chapter, we looked at exceptions and context managers.

We saw that exceptions are Python's way of signaling that an error has occurred. We showed you how to catch exceptions so that your program does not fail when errors inevitably do happen.

We also showed you how you can raise exceptions yourself when your own code detects an error, and that you can even define your own exception types. We saw exception groups and the new syntax that extends the `except` clause. We ended our exploration of exceptions by seeing that they are not only useful for signaling errors but can also be used as a flow-control mechanism.

We ended the chapter with a brief overview of context managers. We saw how to use the `with` statement to enter a context defined by a context manager that performs cleanup operations when we exit the context. We also showed you how to create your own context managers, either as part of a class or by using a generator function.

We will see more context managers in action in the next chapter, which focuses on files and data persistence.

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8

Files and Data Persistence

> *"It is not that I'm so smart, it is just that I stay with problems longer."*
>
> *– Albert Einstein*

In the previous chapters, we explored several different aspects of Python. As the examples have a didactic purpose, we ran them in a simple Python shell or in the form of a Python module. They ran, maybe printed something on the console, and then they terminated, leaving no trace of their brief existence.

Real-world applications are rather different. Naturally, they still run in memory, but they interact with networks, disks, and databases. They also exchange information with other applications and devices, using formats that are suitable for the situation.

In this chapter, we are going to start closing in on the real world by exploring the following:

- Files and directories
- Compression
- Networks and streams
- The JSON data-interchange format
- Data persistence with `pickle` and `shelve` from the standard library
- Data persistence with SQLAlchemy
- Configuration files

As usual, we will try to balance breadth and depth so that by the end of the chapter, you will have a solid grasp of the fundamentals and will know how to fetch further information from the web.

Working with files and directories

When it comes to files and directories, Python offers plenty of useful tools. In the following examples, we will use the `os`, `pathlib`, and `shutil` modules. As we will be reading and writing on the disk, we will be using a file, `fear.txt`, which contains an excerpt from *Fear*, by Thich Nhat Hanh, as a base for some of our examples.

Opening files

Opening a file in Python is simple and intuitive. In fact, we just need to use the `open()` function. Let us see a quick example:

```
# files/open_try.py
fh = open("fear.txt", "rt")  # r: read, t: text

for line in fh.readlines():
    print(line.strip())  # remove whitespace and print

fh.close()
```

The previous code is straightforward. We call `open()`, passing the filename, and telling `open()` that we want to read it in text mode (via the `"rt"` flag). There is no path information before the filename; therefore, `open()` will assume the file is in the same folder the script is run from. This means that if we run this script from outside the `files` folder, then `fear.txt` will not be found.

Once the file has been opened, we obtain a file object, `fh`, which we can use to work on the content of the file. We chose that name because, in Python, a file object is essentially a high-level abstraction that wraps the underlying file handle (`fh`). In this case, we use the `readlines()` method to iterate over all the lines in the file and print them. We call `strip()` on each line to get rid of any extra spaces around the content, including the line termination character at the end, since `print()` will already add one for us. This is a quick and dirty solution that works in this example but should the content of the file contain meaningful spaces that need to be preserved, you will have to be slightly more careful in how you sanitize the data. At the end of the script, we close the stream.

Closing a file is important as we do not want to risk failing to release the handle (`fh`) we have on it. When that happens, you can encounter issues such as memory leaks, or the annoying *"you cannot delete this file"* pop-up that informs you that some software is still using it.

Therefore, we need to apply some precautions and wrap the previous logic in a `try/finally` block. This means that, whatever error might occur when we try to open and read the file, we can rest assured that `close()` will be called:

```
# files/open_try.py
fh = open("fear.txt", "rt")

try:
    for line in fh.readlines():
        print(line.strip())

finally:
    fh.close()
```

The logic is the same, but now it is also safe.

If you are not familiar with the `try/finally` block, make sure you go back to the *Handling Exceptions* section of *Chapter 7*, *Exceptions and Context Managers*, and study it.

We can simplify the previous example further like this:

```
# files/open_try.py
fh = open("fear.txt")  # rt is default

try:
    for line in fh:  # we can iterate directly on fh
        print(line.strip())

finally:
    fh.close()
```

The default mode for opening files is `"rt"`, so we do not need to specify it. Moreover, we can simply iterate on `fh` without explicitly calling `readlines()` on it. Python often gives us shorthands to make our code more compact and simpler to read.

All the previous examples produce a print of the file on the console (check out the source code to read the whole content):

```
An excerpt from Fear - By Thich Nhat Hanh

The Present Is Free from Fear

When we are not fully present, we are not really living. We are not
really there, either for our loved ones or for ourselves. If we are
not there, then where are we? We are running, running, running,
even during our sleep. We run because we are trying to escape from
our fear. […]
```

Using a context manager to open a file

To avoid having to use `try/finally` blocks throughout our code, Python gives us a nicer and equally safe way to do it: by using a context manager. Let us see the code first:

```
# files/open_with.py
with open("fear.txt") as fh:
    for line in fh:
        print(line.strip())
```

This example is equivalent to the previous one but reads better. The `open()` function returns a file object when invoked by a context manager, and it conveniently calls `fh.close()` automatically when execution exits the context manager scope. This will happen even in the case of errors.

Reading from and writing to a file

Now that we know how to open a file, let us see how to read from and write to it:

```
# files/print_file.py
with open("print_example.txt", "w") as fw:
    print("Hey I am printing into a file!!!", file=fw)
```

This first approach uses the `print()` function, with which we are already familiar from previous chapters. After obtaining a file object, this time specifying that we intend to write to it (`"w"`), we can tell the call to `print()` to direct its output to the file, instead of to the **standard output** stream as it normally does.

In Python, the standard input, output, and error streams are represented by the file objects `sys.stdin`, `sys.stdout`, and `sys.stderr`. Unless input or output is redirected, reading from `sys.stdin` usually corresponds to reading from the keyboard, and writing to `sys.stdout` or `sys.stderr` usually prints to the console screen.

The previous code creates the `print_example.txt` file if it does not exist, or truncates it if it does, and writes the line `Hey I am printing into a file!!!` into it.

Truncating a file means erasing its contents without deleting it. After truncation, the file still exists on the filesystem, but it is empty.

This example does the job, but it is not what we would typically do when writing to a file. Let us see a more common approach:

```
# files/read_write.py
with open("fear.txt") as f:
    lines = [line.rstrip() for line in f]

with open("fear_copy.txt", "w") as fw:  # w - write
    fw.write("\n".join(lines))
```

In this example, we first open `fear.txt` and gather its content into a list, line by line. Notice that, this time, we are calling a different method, `rstrip()`, as an example, to make sure we only strip the whitespace on the right-hand side of every line.

In the second part of the snippet, we create a new file, `fear_copy.txt`, and we write to it all the strings in `lines`, joined by a newline, `\n`. Python works by default with **universal newlines**, which means that even though the original file might have a newline that is different from `\n`, it will be translated automatically for us before the line is returned. This behavior is, of course, customizable, but normally it is exactly what we want. Speaking of newlines, can you think of one that might be missing in the copy?

Reading and writing in binary mode

Notice that by opening a file and passing `t` in the options (or omitting it, as it is the default), we are opening the file in text mode. This means that the content of the file is treated and interpreted as text.

If you wish to write bytes to a file, you can open it in **binary mode**. This is a common requirement when you handle files that do not just contain raw text, such as images, audio/video, and, in general, any other proprietary format.

To handle files in binary mode, simply specify the `b` flag when opening them, as in the following example:

```
# files/read_write_bin.py
with open("example.bin", "wb") as fw:
    fw.write(b"This is binary data...")

with open("example.bin", "rb") as f:
    print(f.read())  # prints: b'This is binary data...'
```

In this example, we are still using text as binary data, for simplicity, but it could be anything you want. You can see it is treated as binary by the fact that you get the `b` prefix in the output string.

Protecting against overwriting an existing file

As we have seen, Python gives us the ability to open files for writing. By using the `w` flag, we open a file and truncate its content. This means the file is overwritten with an empty file, and the original content is lost. If you wish to only open a file for writing if it does not already exist, you can use the `x` flag instead, as in the following example:

```
# files/write_not_exists.py
with open("write_x.txt", "x") as fw:  # this succeeds
    fw.write("Writing line 1")

with open("write_x.txt", "x") as fw:  # this fails
    fw.write("Writing line 2")
```

If you run this snippet, you will find a file called `write_x.txt` in your directory, containing only one line of text. The second part of the snippet, in fact, fails to execute. This is the output we get on our console (the file path has been shortened for editorial purposes):

```
$ python write_not_exists.py
Traceback (most recent call last):
  File "write_not_exists.py", line 6, in <module>
    with open("write_x.txt", "x") as fw:  # this fails
         ^^^^^^^^^^^^^^^^^^^^^^^^
FileExistsError: [Errno 17] File exists: 'write_x.txt'
```

As we have seen, there are different modes for opening a file. You can find the full list of flags at `https://docs.python.org/3/library/functions.html#open`.

Checking for file and directory existence

If you want to make sure a file or directory exists (or does not), the `pathlib` module is what you need. Let us see a small example:

```
# files/existence.py
from pathlib import Path

p = Path("fear.txt")
path = p.parent.absolute()

print(p.is_file())  # True
print(path)  # /Users/fab/code/lpp4ed/ch08/files
print(path.is_dir())  # True

q = Path("/Users/fab/code/lpp4ed/ch08/files")
print(q.is_dir())  # True
```

In the preceding snippet, we create a `Path` object that we set up with the name of the text file we want to inspect. We use the `parent()` method to retrieve the folder in which the file is contained, and we call the `absolute()` method on it to extract the absolute path information.

We check if `"fear.txt"` is a file and the folder in which it is contained is indeed a folder (or directory, which is equivalent).

The old way to do these operations was to use the `os.path` module from the standard library. While `os.path` works on strings, `pathlib` offers classes representing filesystem paths with semantics appropriate for different operating systems. Hence, we suggest using `pathlib` whenever possible, and reverting to the old way of doing things only when there is no alternative.

Manipulating files and directories

Let us see a couple of quick examples of how to manipulate files and directories. The first example manipulates the content:

```
# files/manipulation.py
from collections import Counter
from string import ascii_letters
```

```
chars = ascii_letters + " "

def sanitize(s, chars):
    return "".join(c for c in s if c in chars)

def reverse(s):
    return s[::-1]

with open("fear.txt") as stream:
    lines = [line.rstrip() for line in stream]

# let us write the mirrored version of the file
with open("raef.txt", "w") as stream:
    stream.write("\n".join(reverse(line) for line in lines))

# now we can calculate some statistics
lines = [sanitize(line, chars) for line in lines]
whole = " ".join(lines)

# we perform comparisons on the lowercased version of `whole`
cnt = Counter(whole.lower().split())

# we can print the N most common words
print(cnt.most_common(3)) # [('we', 17), ('the', 13), ('were', 7)]
```

This example defines two functions: `sanitize()` and `reverse()`. They are simple functions whose purpose is to remove anything that is not a letter or space from a string and produce the reversed copy of a string, respectively.

We open `fear.txt` and we read its content into a list. Then we create a new file, `raef.txt`, which will contain the horizontally mirrored version of the original. We write all the content of `lines` with a single operation, using `join` on a newline character. Maybe more interesting is the bit at the end. First, we reassign `lines` to a sanitized version of itself by means of a list comprehension. Then we put the lines together in the `whole` string, and finally, we pass the result to a `Counter` object. Notice that we split the lowercase version of the string into a list of words. This way, each word will be counted correctly, regardless of its case, and, thanks to `split()`, we don't need to worry about extra spaces anywhere. When we print the three most common words, we realize that, truly, Thich Nhat Hanh's focus was on others, as *"we"* is the most common word in the text:

```
$ python manipulation.py
[('we', 17), ('the', 13), ('were', 7)]
```

Let us now see an example of manipulation that's more related to disk operations, in which we put the `shutil` module to use:

```
# files/ops_create.py
import shutil
from pathlib import Path

base_path = Path("ops_example")

# let us perform an initial cleanup just in case
if base_path.exists() and base_path.is_dir():
    shutil.rmtree(base_path)

# now we create the directory
base_path.mkdir()

path_b = base_path / "A" / "B"
path_c = base_path / "A" / "C"
path_d = base_path / "A" / "D"

path_b.mkdir(parents=True)
path_c.mkdir()  # no need for parents now, as 'A' has been created

# we add three files in `ops_example/A/B`
for filename in ("ex1.txt", "ex2.txt", "ex3.txt"):
    with open(path_b / filename, "w") as stream:
        stream.write(f"Some content here in {filename}\n")

shutil.move(path_b, path_d)

# we can also rename files
ex1 = path_d / "ex1.txt"
ex1.rename(ex1.parent / "ex1.renamed.txt")
```

In the preceding code, we start by declaring a base path, which will contain all the files and folders we are going to create. We then use `mkdir()` to create two directories: `ops_example/A/B` and `ops_example/A/C`. Notice that we don't need to specify `parents=True` when calling `path_c.mkdir()`, since all the parents have already been created by the previous call on `path_b`.

We use the `/` operator to concatenate directory names; `pathlib` takes care of using the right path separator for us, behind the scenes.

After creating the directories, we loop to create three files in directory `B`. Then, we move directory `B` and its contents to a different name: `D`. We also could have done this in another way: `path_b.rename(path_d)`.

Finally, we rename `ex1.txt` to `ex1.renamed.txt`. If you open that file, you will see it still contains the original text from the loop logic. Calling `tree` on the result produces the following:

```
$ tree ops_example
ops_example
└── A
    ├── C
    └── D
        ├── ex1.renamed.txt
        ├── ex2.txt
        └── ex3.txt
```

Manipulating pathnames

Let us explore the abilities of `pathlib` a little more by means of an example:

```
# files/paths.py
from pathlib import Path

p = Path("fear.txt")

print(p.absolute())
print(p.name)
print(p.parent.absolute())
print(p.suffix)

print(p.parts)
print(p.absolute().parts)
```

```
readme_path = p.parent / ".." / ".." / "README.rst"
print(readme_path.absolute())
print(readme_path.resolve())
```

Reading the result is probably a good enough explanation for this simple example:

```
$ python paths.py
/Users/fab/code/lpp4ed/ch08/files/fear.txt
fear.txt
/Users/fab/code/lpp4ed/ch08/files
.txt
('fear.txt',)
(
    '/', 'Users', 'fab', 'code', 'lpp4ed',
    'ch08', 'files', 'fear.txt'
)
/Users/fab/code/lpp4ed/ch08/files/../../README.rst
/Users/fab/code/lpp4ed/README.rst
```

Note how, in the last two lines, we have two different representations of the same path. The first one (`readme_path.absolute()`) shows two `".."`, each of which, in path terms, indicates changing to the parent folder. So, by changing to the parent folder twice in a row, from `…/lpp4e/ch08/files/`, we go back to `…/lpp4e/`. This is confirmed by the last line in the example, which shows the output of `readme_path.resolve()`.

Temporary files and directories

Sometimes, it is useful to create a temporary directory or file. For example, when writing tests that affect the disk, you can use temporary files and directories to run your logic and assert that it is correct, and to be sure that at the end of the test run, the test folder has no leftovers. Let us see how to do it in Python:

```
# files/tmp.py
from tempfile import NamedTemporaryFile, TemporaryDirectory

with TemporaryDirectory(dir=".") as td:
    print("Temp directory:", td)
    with NamedTemporaryFile(dir=td) as t:
        name = t.name
        print(name)
```

The preceding example is quite straightforward: we create a temporary directory in the current one (`"."`), and we create a named temporary file in it. We print the filename, as well as its full path:

```
$ python tmp.py
Temp directory: /Users/fab/code/lpp4ed/ch08/files/tmpqq4quhbc
/Users/fab/code/lpp4ed/ch08/files/tmpqq4quhbc/tmpypwwhpwq
```

Running this script will produce a different result every time as these are temporary random names.

Directory content

With Python, you can also inspect the contents of a directory. We will show you two ways of doing this. This is the first one:

```
# files/listing.py
from pathlib import Path

p = Path(".")

for entry in p.glob("*"):
    print("File:" if entry.is_file() else "Folder:", entry)
```

This snippet uses the `glob()` method of a `Path` object, applied from the current directory. We iterate over the results, each of which is an instance of a subclass of `Path` (`PosixPath` or `WindowsPath`, according to which OS we are running). For each `entry`, we inspect if it is a directory, and print accordingly. Running the code yields the following (we omitted a few results for brevity):

```
$ python listing.py
File: existence.py
File: manipulation.py
…
File: open_try.py
File: walking.pathlib.py
```

An alternative way is to use the `Path.walk()` method to scan a directory tree. Let us see an example:

```
# files/walking.pathlib.py
from pathlib import Path

p = Path(".")
```

```
for root, dirs, files in p.walk():
    print(f"{root=}")

    if dirs:
        print("Directories:")
        for dir_ in dirs:
            print(dir_)
        print()

    if files:
        print("Files:")
        for filename in files:
            print(filename)
        print()
```

Running the preceding snippet will produce a list of all the files and directories in the current one, and it will do the same for each sub-directory. In the source code for this book, you will find another module, `walking.py`, which does exactly the same but uses the `os.walk()` function instead.

File and directory compression

Before we leave this section, let us give you an example of how to create a compressed file. In the source code for this chapter, in the `files/compression` folder, we have two examples: one creates a `.zip` file, while the other one creates a `tar.gz` file. Python allows you to create compressed files in several different ways and formats. Here, we are going to show you how to create the most common one, **ZIP**:

```
# files/compression/zip.py
from zipfile import ZipFile

with ZipFile("example.zip", "w") as zp:
    zp.write("content1.txt")
    zp.write("content2.txt")
    zp.write("subfolder/content3.txt")
    zp.write("subfolder/content4.txt")

with ZipFile("example.zip") as zp:
    zp.extract("content1.txt", "extract_zip")
    zp.extract("subfolder/content3.txt", "extract_zip")
```

In the preceding code, we import `ZipFile`, and then, within a context manager, we write into it four files (two of which are in a sub-folder, to show how ZIP preserves the full path). Afterward, as an example, we open the compressed file and extract a couple of files from it into the `extract_zip` directory. If you are interested in learning more about data compression, make sure you check out the *Data Compression and Archiving* section on the standard library (`https://docs.python.org/3.9/library/archiving.html`), where you'll be able to learn all about this topic.

Data interchange formats

Modern software architectures tend to split an application into several components. Whether you embrace the service-oriented architecture paradigm or push it even further into the microservices realm, these components will have to exchange data. But even if you are coding a monolithic application whose codebase is contained in one project, chances are that you still have to exchange data with APIs or programs, or simply handle the data flow between the frontend and backend parts of your website, which likely won't speak the same language.

Choosing the right format in which to exchange information is crucial. A language-specific format has the advantage that the language itself is likely to provide you with all the tools to make **serialization** and **deserialization** a breeze. However, you will lack the ability to talk natively to other components that have been written in different versions of the same language, or in different languages altogether. Regardless of what the future looks like, going with a language-specific format should only be done if it is the only possible choice for the given situation.

According to Wikipedia (`https://en.wikipedia.org/wiki/Serialization`):

> *In computing, serialization is the process of translating a data structure or object state into a format that can be stored (for example, in a file or memory data buffer) or transmitted (for example, over a computer network) and reconstructed later (possibly in a different computer environment).*

A safer approach is to choose a language-agnostic format. In software, some popular formats have become the de facto standard for data interchange. The most famous ones probably are **XML**, **YAML**, and **JSON**. The Python standard library features the `xml` and `json` modules, and, on PyPI (`https://pypi.org/`), you can find a few different packages to work with YAML.

In the Python environment, JSON is perhaps the most commonly used format. It wins over the other two because of being part of the standard library, and for its simplicity. XML tends to be quite verbose, and harder to read.

Moreover, when working with a database like PostgreSQL, the ability to use native JSON fields makes a compelling case for adopting JSON in the application as well.

Working with JSON

JSON is the acronym for **JavaScript Object Notation**, and it is a subset of the JavaScript language. It has been around for almost two decades now, so it is well known and widely adopted by most languages, even though it is actually language independent. You can read all about it on its website (`https://www.json.org/`), but we are going to give you a quick introduction to it now.

JSON is based on two structures:

- A collection of name/value pairs
- An ordered list of values

Unsurprisingly, these two objects map to the `dict` and `list` data types in Python, respectively. As data types, JSON offers strings, numbers, objects, and values consisting of `true`, `false`, and `null`. Let us see a quick example to get us started:

```
# json_examples/json_basic.py
import sys
import json

data = {
    "big_number": 2**3141,
    "max_float": sys.float_info.max,
    "a_list": [2, 3, 5, 7],
}

json_data = json.dumps(data)
data_out = json.loads(json_data)

assert data == data_out  # json and back, data matches
```

We begin by importing the `sys` and `json` modules. Then, we create a simple dictionary with some numbers and a list of integers. We wanted to test serializing and deserializing using very big numbers, both `int` and `float`, so we put 2^{3141} and whatever is the biggest floating point number our system can handle.

We serialize with `json.dumps()`, which converts data into a JSON formatted string. That data is then fed into `json.loads()`, which does the opposite: from a JSON formatted string, it reconstructs the data into Python.

Notice that the JSON module also provides the `dump` and `load` functions, which convert data to and from a file-like object.

On the last line, by means of an assertion, we make sure that the original data and the result of the serialization/deserialization through JSON match. Should the condition that follows the assert statement be falsy, that statement will raise an `AssertionError`. We will cover assertions in more detail in *Chapter 10*, *Testing*.

In programming, the term **falsy** refers to an object or a condition that, when evaluated in a boolean context, is considered false.

Let us see what JSON data would look like if we printed it:

```
# json_examples/json_basic.py
info = {
    "full_name": "Sherlock Holmes",
    "address": {
        "street": "221B Baker St",
        "zip": "NW1 6XE",
        "city": "London",
        "country": "UK",
    },
}

print(json.dumps(info, indent=2, sort_keys=True))
```

In this example, we create a dictionary with Sherlock Holmes' data in it. If, like us, you are a fan of Sherlock Holmes, and are in London, you will find his museum at that address (which we recommend visiting; it is small but very nice).

Notice how we call `json.dumps()`, though. We instruct it to indent with two spaces and sort keys alphabetically. The result is this:

```
$ python json_basic.py
{
  "address": {
    "city": "London",
    "country": "UK",
    "street": "221B Baker St",
    "zip": "NW1 6XE"
  },
  "full_name": "Sherlock Holmes"
}
```

The similarity with Python is evident. The one difference is that if you place a comma on the last element in a dictionary, as is customary in Python, JSON will complain.

Let us show you something interesting:

```
# json_examples/json_tuple.py
import json

data_in = {
    "a_tuple": (1, 2, 3, 4, 5),
}

json_data = json.dumps(data_in)
print(json_data)  # {"a_tuple": [1, 2, 3, 4, 5]}
data_out = json.loads(json_data)
print(data_out)  # {'a_tuple': [1, 2, 3, 4, 5]}
```

In this example, we have used a tuple instead of a list. The interesting bit is that, conceptually, a tuple is also an ordered list of items. It does not have the flexibility of a list, but still, it is considered the same from the perspective of JSON. Therefore, as you can see by the first `print()`, in JSON a tuple is transformed into a list. Naturally, then, the information that the original object was a tuple is lost, and when deserialization happens, what originally was a tuple is instead translated to a Python list. It is important that you keep this in mind when dealing with data, as going through a transformation process that involves a format that only comprises a subset of the data structures you can use implies there may be information loss. In this case, we lost the information about the type (tuple versus list).

This is actually a common problem. For example, you cannot serialize all Python objects to JSON, as it is not always clear how JSON should revert that object. Think about `datetime`, for example. An instance of that class is a Python object that JSON will not be able to serialize. If we transform it into a string such as `2018-03-04T12:00:30Z`, which is the ISO 8601 representation of a date with time and time zone information, what should JSON do when deserializing? Should it decide that *this is deserializable into a datetime object, so I'd better do it*, or should it simply consider it as a string and leave it as it is? What about data types that can be interpreted in more than one way?

The answer is that when dealing with data interchange, we often need to transform our objects into a simpler format prior to serializing them with JSON. The more we manage to simplify our data, the easier it is to represent that data in a format like JSON, which has limitations.

In some cases, though, and mostly for internal use, it is useful to be able to serialize custom objects, so, just for fun, we are going to show you how with two examples: complex numbers and *datetime* objects.

Custom encoding/decoding with JSON

In the JSON world, we can consider terms like encoding/decoding as synonyms for serializing/deserializing. They basically mean transforming to and back from JSON.

In the following example, we are going to learn how to encode complex numbers – which are not serializable to JSON by default – by writing a custom encoder:

```
# json_examples/json_cplx.py
import json

class ComplexEncoder(json.JSONEncoder):
    def default(self, obj):
        print(f"ComplexEncoder.default: {obj=}")
        if isinstance(obj, complex):
            return {
                "_meta": "complex",
                "num": [obj.real, obj.imag],
            }
        return super().default(obj)

data = {
    "an_int": 42,
    "a_float": 3.14159265,
```

```
    "a_complex": 3 + 4j,
}

json_data = json.dumps(data, cls=ComplexEncoder)
print(json_data)

def object_hook(obj):
    print(f"object_hook: {obj=}")
    try:
        if obj["_meta"] == "complex":
            return complex(*obj["num"])
    except KeyError:
        return obj

data_out = json.loads(json_data, object_hook=object_hook)
print(data_out)
```

We start by defining a `ComplexEncoder` class as a subclass of `JSONEncoder`. This class overrides the `default()` method. This method is called whenever the encoder encounters an object that it cannot encode natively and is expected to return an encodable representation of that object.

The `default()` method checks whether its argument is a `complex` object, in which case it returns a dictionary with some custom meta information and a list that contains both the real and the imaginary part of the number. That is all we need to do to avoid losing information for a complex number. If we receive anything other than an instance of `complex`, we call the `default()` method from the parent class.

In the example, we then call `json.dumps()`, but this time we use the `cls` argument to specify the custom encoder. Finally, the result is printed:

```
$ python json_cplx.py
ComplexEncoder.default: obj=(3+4j)
{
    "an_int": 42, "a_float": 3.14159265,
    "a_complex": {"_meta": "complex", "num": [3.0, 4.0]}
}
```

Half the job is done. For the deserialization part, we could have written another class that would inherit from `JSONDecoder`, but instead, we have chosen to use a different technique that is simpler and uses a small function: `object_hook()`.

Within the body of `object_hook()`, we find a `try` block. The important part is the two lines within the body of the `try` block itself. The function receives an object (note that the function is only called when `obj` is a dictionary), and if the metadata matches our convention for complex numbers, we pass the real and imaginary parts to the `complex()` function. The `try/except` block is there because our function will be called for every dictionary object that is decoded, so we need to handle the case where our `_meta` key is not present.

The decoding part of the example outputs:

```
object_hook:
  obj={'_meta': 'complex', 'num': [3.0, 4.0]}
object_hook:
  obj={'an_int': 42, 'a_float': 3.14159265, 'a_complex': (3+4j)}
{'an_int': 42, 'a_float': 3.14159265, 'a_complex': (3+4j)}
```

You can see that `a_complex` has been correctly deserialized. As an exercise, we suggest writing your own custom encoders for `Fraction` and `Decimal` objects.

Let us now consider a slightly more complex (no pun intended) example: dealing with `datetime` objects. We are going to split the code into two blocks, first the serializing part, and then the deserializing part:

```
# json_examples/json_datetime.py
import json
from datetime import datetime, timedelta, timezone

now = datetime.now()
now_tz = datetime.now(tz=timezone(timedelta(hours=1)))

class DatetimeEncoder(json.JSONEncoder):
    def default(self, obj):
        if isinstance(obj, datetime):
            try:
                off = obj.utcoffset().seconds
            except AttributeError:
                off = None

            return {
                "_meta": "datetime",
```

```
                "data": obj.timetuple()[:6] + (obj.microsecond,),
                "utcoffset": off,
            }
        return super().default(obj)

data = {
    "an_int": 42,
    "a_float": 3.14159265,
    "a_datetime": now,
    "a_datetime_tz": now_tz,
}

json_data = json.dumps(data, cls=DatetimeEncoder)
print(json_data)
```

The reason this example is slightly more complex lies in the fact that `datetime` objects in Python can either be time-zone-aware or not; therefore, we need to handle them carefully. The flow is as before, only we are dealing with a different data type. We start by getting the current date and time information, and we do it both without (`now`) and with (`now_tz`) time zone awareness. We then proceed to define a custom encoder as before, overriding the `default()` method. The important bits in that method are how we get the time zone offset (`off`) information, in seconds, and how we structure the dictionary that returns the data. This time, the metadata says it is *datetime* information. We save the first six items from the time tuple (year, month, day, hour, minute, and second), plus the microseconds in the `data` key, and the offset after that. Good job if you could tell that the value of `"data"` is a concatenation of tuples.

After the custom encoder, we proceed to create some data, and then we serialize it. The `print()` statement outputs the following (we have reformatted the output to make it more readable):

```
$ python json_datetime.py
{
    "an_int": 42,
    "a_float": 3.14159265,
    "a_datetime": {
        "_meta": "datetime",
        "data": [2024, 3, 29, 23, 24, 22, 232302],
        "utcoffset": null,
    },
```

```
    "a_datetime_tz": {
        "_meta": "datetime",
        "data": [2024, 3, 30, 0, 24, 22, 232316],
        "utcoffset": 3600,
    },
}
```

Interestingly, we find out that `None` is translated to `null`, its JavaScript equivalent. Moreover, we can see that the data seems to have been encoded properly. Let us proceed with the second part of the script:

```
# json_examples/json_datetime.py
def object_hook(obj):
    try:
        if obj["_meta"] == "datetime":
            if obj["utcoffset"] is None:
                tz = None
            else:
                tz = timezone(timedelta(seconds=obj["utcoffset"]))
            return datetime(*obj["data"], tzinfo=tz)
    except KeyError:
        return obj

data_out = json.loads(json_data, object_hook=object_hook)
print(data_out)
```

Once again, we first verify that the metadata is telling us it is a `datetime`, and then we proceed to fetch the time zone information. Once we have it, we pass the 7-tuple (using `*` to unpack its values in the call) and the time zone information to the `datetime()` call, getting back our original object. Let us verify it by printing `data_out`:

```
{
    "an_int": 42,
    "a_float": 3.14159265,
    "a_datetime": datetime.datetime(
        2024, 3, 29, 23, 24, 22, 232302
    ),
    "a_datetime_tz": datetime.datetime(
        2024, 3, 30, 0, 24, 22, 232316,
```

```
        tzinfo=datetime.timezone(
            datetime.timedelta(seconds=3600)
        ),
    ),
}
```

As you can see, we got everything back correctly. As an exercise, we suggest you write the same logic but for a `date` object, which should be simpler.

Before we move on to the next topic, a word of caution. Perhaps it is counter-intuitive, but working with `datetime` objects can be quite tricky, so although we are pretty sure this code is doing what it is supposed to do, we want to stress that we only tested it superficially. So, if you intend to use it, please do test it thoroughly. Test for different time zones, test for daylight saving time being on and off, test for dates before the epoch, and so on. You might find that the code in this section needs some modifications to suit your case.

I/O, streams, and requests

I/O stands for **input/output**, and it broadly refers to the communication between a computer and the outside world. There are several different types of I/O, and it is outside the scope of this chapter to explain all of them, but it is worth going through a couple of examples. The first one will introduce the `io.StringIO` class, which is an in-memory stream for text I/O. The second one instead will escape the locality of our computer and demonstrate how to perform an HTTP request.

Using an in-memory stream

In-memory objects can be useful in a multitude of situations. Memory is much faster than a hard disk, it is always available, and for small amounts of data can be the perfect choice.

Let us see the first example:

```
# io_examples/string_io.py
import io

stream = io.StringIO()
stream.write("Learning Python Programming.\n")
print("Become a Python ninja!", file=stream)

contents = stream.getvalue()
print(contents)
```

```
stream.close()
```

In the preceding code snippet, we import the `io` module from the standard library. This module features many tools related to streams and I/O. One of them is `StringIO`, which is an in-memory buffer in which we have written two sentences, using two different methods, as we did with files in the first examples of this chapter.

`StringIO` is useful when you need to:

- Simulate file-like behavior for strings.
- Test code that works with file-like objects without using actual files.
- Build or manipulate large strings efficiently.
- Capture or mock input/output for testing purposes. Tests run much faster because they avoid disk I/O.

We can either call `StringIO.write()` or we can use `print()`, instructing it to direct the data to our stream.

By calling `getvalue()`, we can get the content of the stream. We then proceed to print it, and finally, we close it. The call to `close()` causes the text buffer to be immediately discarded.

There is a more elegant way to write the previous code:

```
# io_examples/string_io.py
with io.StringIO() as stream:
    stream.write("Learning Python Programming.\n")
    print("Become a Python ninja!", file=stream)

    contents = stream.getvalue()
    print(contents)
```

Like the built-in `open()`, `io.StringIO()` too works well within a context manager block. Notice the similarity with `open()`; in this case as well, we don't need to manually close the stream.

When running the script, the output is:

```
$ python string_io.py
Learning Python Programming.
Become a Python ninja!
```

Let us now proceed with the second example.

Making HTTP requests

In this section, we explore two examples of HTTP requests. We will use the `requests` library for these examples, which you can install with `pip`, and it is included in the requirements file for this chapter.

We are going to perform HTTP requests against the httpbin.org (`https://httpbin.org/`) API, which, interestingly, was developed by Kenneth Reitz, the creator of the `requests` library. Httpbin is a simple HTTP request and response service that is useful when we want to experiment with the HTTP protocol.

This library is among the most widely adopted:

```
# io_examples/reqs.py
import requests

urls = {
    "get": "https://httpbin.org/get?t=learn+python+programming",
    "headers": "https://httpbin.org/headers",
    "ip": "https://httpbin.org/ip",
    "user-agent": "https://httpbin.org/user-agent",
    "UUID": "https://httpbin.org/uuid",
    "JSON": "https://httpbin.org/json",
}

def get_content(title, url):
    resp = requests.get(url)
    print(f"Response for {title}")
    print(resp.json())

for title, url in urls.items():
    get_content(title, url)
    print("-" * 40)
```

The preceding snippet should be straightforward. We declare a dictionary of URLs against which we want to perform HTTP requests. We have encapsulated the code that performs the request into the `get_content()` function. As you can see, we perform a GET request (by using `requests.get()`), and we print the title and the JSON-decoded version of the body of the response. Let us spend a few words on this last bit.

When we perform a request to a website, or to an API, we get back a response object encapsulating the data that was returned by the server we performed the request against. The body of some responses from `httpbin.org` happens to be JSON encoded, so instead of getting the body as it is (by reading `resp.text`) and manually decoding it by calling `json.loads()` on it, we simply combine the two by using the `json()` method of the response object. There are plenty of reasons why the `requests` package has become so widely adopted, and one of them is its ease of use.

Now, when you perform a request in your application, you will want to have a much more robust approach for dealing with errors and so on, but for this chapter, a simple example will do. We will see more examples of requests in *Chapter 14*, *Introduction to API Development*.

Going back to our code, in the end, we run a `for` loop and get all the URLs. When you run it, you will see the result of each call printed on your console, which should look like this (prettified and trimmed for brevity):

```
$ python reqs.py
Response for get
{
    "args": {"t": "learn python programming"},
    "headers": {
        "Accept": "*/*",
        "Accept-Encoding": "gzip, deflate",
        "Host": "httpbin.org",
        "User-Agent": "python-requests/2.31.0",
        "X-Amzn-Trace-Id": "Root=1-123abc-123abc",
    },
    "origin": "86.14.44.233",
    "url": "https://httpbin.org/get?t=learn+python+programming",
}
… rest of the output omitted …
```

Notice that you might get a slightly different output in terms of version numbers and IPs, which is fine. Now, `GET` is only one of the HTTP verbs, albeit one of the most commonly used. Let us also look at how to use the `POST` verb. This is the type of request you make when you need to send data to the server, for example, to request the creation of a resource. Every time you submit a form on the web, you are making a `POST` request. So, let us try to make one programmatically:

```
# io_examples/reqs_post.py
import requests
```

```
url = "https://httpbin.org/post"
data = dict(title="Learn Python Programming")

resp = requests.post(url, data=data)
print("Response for POST")
print(resp.json())
```

The preceding code is very similar to what we saw before, only this time we don't call `get()`, but `post()`, and because we want to send some data, we specify that in the call. The `requests` library offers much more than this. It is a project that we encourage you to check out and explore, as it is quite likely you will be using it too.

Running the previous script (and applying some prettifying magic to the output) yields the following:

```
$ python reqs_post.py
Response for POST
{
    "args": {},
    "data": "",
    "files": {},
    "form": {"title": "Learn Python Programming"},
    "headers": {
        "Accept": "*/*",
        "Accept-Encoding": "gzip, deflate",
        "Content-Length": "30",
        "Content-Type": "application/x-www-form-urlencoded",
        "Host": "httpbin.org",
        "User-Agent": "python-requests/2.31.0",
        "X-Amzn-Trace-Id": "Root=1-123abc-123abc",
    },
    "json": None,
    "origin": "86.14.44.233",
    "url": "https://httpbin.org/post",
}
```

Notice how the headers are now different, and we find the data we sent in the form of a key/value pair of the response body.

We hope these short examples are enough to get you started, especially with requests. The web changes every day, so it is worth learning the basics and then brushing up every now and then.

Persisting data on disk

In this section of this chapter, we will look at how to persist data on disk in three different formats. To persist data means that the data is written to non-volatile storage, like a hard drive, for example, and it is not deleted when the process that wrote it ends its life cycle. We will explore the `pickle` and `shelve` modules, as well as a short example that will involve accessing a database using **SQLAlchemy**, perhaps the most widely adopted ORM library in the Python ecosystem.

Serializing data with pickle

The `pickle` module, from the Python standard library, offers tools to convert Python objects into byte streams, and vice versa. Even though there is a partial overlap in the API that `pickle` and `json` expose, the two are quite different. As we have seen previously in this chapter, JSON is a text format that is human readable, language independent, and supports only a restricted subset of Python data types. The `pickle` module, on the other hand, is not human readable, translates to bytes, is Python-specific, and, thanks to the wonderful Python introspection capabilities, supports a large number of data types.

Besides these differences between `pickle` and `json`, there are also some important security concerns that you need to be aware of if you are considering using `pickle`. *Unpickling* erroneous or malicious data from an untrusted source can be dangerous, so if we decide to adopt it in our application, we need to be extra careful.

If you do use `pickle`, you should consider using a cryptographic signature to ensure that your pickled data has not been tampered with. We will see how to generate cryptographic signatures in Python in *Chapter 9*, *Cryptography and Tokens*.

That said, let us see it in action by means of a simple example:

```
# persistence/pickler.py
import pickle
from dataclasses import dataclass

@dataclass
class Person:
    first_name: str
```

```
    last_name: str
    id: int

    def greet(self):
        print(
            f"Hi, I am {self.first_name} {self.last_name}"
            f" and my ID is {self.id}"
        )

people = [
    Person("Obi-Wan", "Kenobi", 123),
    Person("Anakin", "Skywalker", 456),
]

# save data in binary format to a file
with open("data.pickle", "wb") as stream:
    pickle.dump(people, stream)

# load data from a file
with open("data.pickle", "rb") as stream:
    peeps = pickle.load(stream)

for person in peeps:
    person.greet()
```

In this example, we create a `Person` class using the `dataclass` decorator, which we saw in *Chapter 6, OOP, Decorators, and Iterators*. The only reason we wrote this example using `dataclass` is to show you how effortlessly `pickle` deals with it, with no need for us to do anything we would not do for a simpler data type.

The class has three attributes: `first_name`, `last_name`, and `id`. It also exposes a `greet()` method, which prints a hello message with the instance data.

We create a list of instances and save it to a file. In order to do so, we use `pickle.dump()`, to which we feed the content to be *pickled*, and the stream to which we want to write. Immediately after that, we read from that same file, using `pickle.load()` to convert the entire content of the stream back into Python objects. To make sure that the objects have been converted correctly, we call the `greet()` method on both of them. The result is the following:

```
$ python pickler.py
Hi, I am Obi-Wan Kenobi and my ID is 123
Hi, I am Anakin Skywalker and my ID is 456
```

The `pickle` module also allows you to convert to (and from) byte objects, by means of the `dumps()` and `loads()` functions (note the `s` at the end of both names). In day-to-day applications, `pickle` is usually used when we need to persist Python data that is not supposed to be exchanged with another application. One example we stumbled upon a few years ago was the session manager of a `flask` plugin, which pickles the session object before storing it in a Redis database. In practice, though, you are unlikely to have to deal with this library very often.

Another tool that is possibly used even less, but that proves to be useful when you are short on resources, is `shelve`.

Saving data with shelve

A "shelf" is a persistent dictionary-like object. The beauty of it is that the values you save into a shelf can be any objects you can `pickle`, so you're not restricted like you would be if you were using a database. Albeit interesting and useful, the `shelve` module is used quite rarely in practice. Just for completeness, let us see a quick example of how it works:

```
# persistence/shelf.py
import shelve

class Person:
    def __init__(self, name, id):
        self.name = name
        self.id = id

with shelve.open("shelf1.shelve") as db:
    db["obi1"] = Person("Obi-Wan", 123)
    db["ani"] = Person("Anakin", 456)
    db["a_list"] = [2, 3, 5]
    db["delete_me"] = "we will have to delete this one..."
    print(
        list(db.keys())
    )  # ['ani', 'delete_me', 'a_list', 'obi1']

    del db["delete_me"]  # gone!
```

```
    print(list(db.keys()))  # ['ani', 'a_list', 'obi1']
    print("delete_me" in db)  # False
    print("ani" in db)  # True

    a_list = db["a_list"]
    a_list.append(7)
    db["a_list"] = a_list
    print(db["a_list"])  # [2, 3, 5, 7]
```

Apart from the wiring and the boilerplate around it, this example resembles an exercise with dictionaries. We create a `Person` class and then we open a `shelve` file within a context manager. As you can see, we use the dictionary syntax to store four objects: two `Person` instances, a list, and a string. If we print the keys, we get a list containing the four keys we used. Immediately after printing it, we delete the (aptly named) `delete_me` key/value pair from the shelf. Printing the keys again shows the deletion has succeeded. We then test a couple of keys for membership and, finally, we append number `7` to `a_list`. Notice how we have to extract the list from the shelf, modify it, and save it again.

There is another way to open a shelf that speeds up the process a bit:

```
# persistence/shelf.py
with shelve.open("shelf2.shelve", writeback=True) as db:
    db["a_list"] = [11, 13, 17]
    db["a_list"].append(19)  # in-place append!
    print(db["a_list"])  # [11, 13, 17, 19]
```

By opening the shelf with `writeback=True`, we enable the `writeback` feature, which allows us to simply append to `a_list` as if it was a value within a regular dictionary. The reason this feature is not active by default is that it comes with a price that you pay in terms of memory consumption and slower closing of the shelf.

Now that we have paid homage to the standard library modules related to data persistence, let us look at one of the most widely adopted ORMs in the Python ecosystem: SQLAlchemy.

Saving data to a database

For this example, we are going to work with an in-memory database, which will make things simpler for us. In the source code of the book, we have left a couple of comments to show you how to generate a SQLite file, so we hope you'll explore that option as well.

You can find a free database browser for SQLite at `https://dbeaver.io/`. DBeaver is a free multi-platform database tool for developers, database administrators, analysts, and all people who need to work with databases. It supports all popular databases: MySQL, PostgreSQL, SQLite, Oracle, DB2, SQL Server, Sybase, MS Access, Teradata, Firebird, Apache Hive, Phoenix, Presto, etc.

Before we dive into the code, allow us to briefly introduce the concept of a relational database.

A relational database is a database that allows you to save data following the **relational model**, invented in 1969 by Edgar F. Codd. In this model, data is stored in one or more tables. Each table has rows (also known as **records**, or **tuples**), each of which represents an entry in the table. Tables also have columns (also known as **attributes**), each of which represents an attribute of the records. Each record is identified through a unique key, more commonly known as the **primary key**, which consists of one or more columns in the table. To give you an example: imagine a table called `Users`, with columns `id`, `username`, `password`, `name`, and `surname`.

Such a table would be suitable for containing users of our system; each row would represent a different user. For example, a row with the values `3`, `fab`, `my_wonderful_pwd`, `Fabrizio`, and `Romano` would represent Fabrizio's user in the system.

The model is called *relational* because you can establish relations between tables. For example, if you added a table called `PhoneNumbers` to this database, you could insert phone numbers into it, and then, through a relation, establish which phone number belongs to which user.

To query a relational database, we need a special language. The main standard is called **SQL**, which stands for **Structured Query Language**. It originates from **relational algebra**, which is a formal system and theoretical framework for manipulating and querying data stored in relational databases. The most common operations you can perform usually involve filtering on the rows or columns, joining tables, aggregating the results according to some criteria, and so on. To give you an example in English, a query on our imaginary database could be: *Fetch all users (username, name, surname) whose username starts with "m" and who have at most one phone number*. In this example, we are querying for a subset of the rows in the database, and are only interested in three of the columns in the `User` table for the results. We are filtering on users by taking only those whose username starts with the letter *m*, and even further, only those who have at most one phone number.

Each database comes with its own *flavor* of SQL. They all respect the standard to some extent, but none fully do, and they are all different from one another in some respects. This poses an issue in modern software development. If our application contained raw SQL code, it is quite likely that if we decided to use a different database engine, or maybe a different version of the same engine, we would need to amend the SQL code in our application.

This can be quite painful, especially since SQL queries can be quite complex. To alleviate this issue, computer scientists have created code that maps objects of a programming language to tables of a relational database. Unsurprisingly, the name of such a tool is **Object-Relational Mapping** (**ORM**).

In modern application development, one would normally start interacting with a database by using an ORM. Should they then find themselves in a situation where they cannot perform a certain query through the ORM, they would then, and only then, resort to using SQL directly. This is a good compromise between having no SQL at all and using no ORM, which means specializing the code that interacts with the database, with the aforementioned disadvantages.

In this section, we would like to show an example that leverages SQLAlchemy, one of the most popular third-party Python ORMs. You will have to install it into the virtual environment for this chapter. We are going to define two models (`Person` and `Email`), each of which maps to a table, and then we are going to populate the database and perform a few queries on it.

Let us start with the model declarations:

```
# persistence/alchemy_models.py
from sqlalchemy import ForeignKey, String, Integer
from sqlalchemy.orm import (
    DeclarativeBase,
    mapped_column,
    relationship,
)
```

At the beginning, we import some functions and types. We then proceed to write the `Person` and `Email` classes, as well as the mandatory base class for them. Let us see these definitions:

```
# persistence/alchemy_models.py
class Base(DeclarativeBase):
    pass

class Person(Base):
    __tablename__ = "person"
```

```
    id = mapped_column(Integer, primary_key=True)
    name = mapped_column(String)
    age = mapped_column(Integer)
    emails = relationship(
        "Email",
        back_populates="person",
        order_by="Email.email",
        cascade="all, delete-orphan",
    )

    def __repr__(self):
        return f"{self.name}(id={self.id})"

class Email(Base):
    __tablename__ = "email"

    id = mapped_column(Integer, primary_key=True)
    email = mapped_column(String)
    person_id = mapped_column(ForeignKey("person.id"))
    person = relationship("Person", back_populates="emails")

    def __str__(self):
        return self.email
    __repr__ = __str__
```

Each model inherits from the `Base` class, which in this example is a simple class that inherits from SQLAlchemy's `DeclarativeBase`. We define `Person`, which maps to a table called `"person"`, and exposes the attributes `id`, `name`, and `age`. We also declare a relationship with the `Email` model, by stating that accessing the `emails` attribute will fetch all the entries in the `Email` table that are related to the particular `Person` instance we are dealing with. The `cascade` option affects how creation and deletion work, but it is a more advanced concept, so we suggest you ignore it for now and maybe investigate more later.

The last thing we declare is the `__repr__()` method, which provides us with the official string representation of an object. This is supposed to be a representation that can be used to completely reconstruct the object, but in this example, we simply use it to provide something as output. Python redirects `repr(obj)` to a call to `obj.__repr__()`.

We also declare the `Email` model, which maps to a table called `"email"` and will contain email addresses, and a reference to the person they belong to. You can see the `person_id` and `person` attributes are both about setting a relation between the `Email` and `Person` classes. Note also how we declare the `__str__()` method on `Email`, and then assign an alias to it, called `__repr__()`. This means that calling either `repr()` or `str()` on `Email` objects will ultimately result in calling the `__str__()` method. This is quite a common technique in Python, used to avoid duplicating the same code, so we took the opportunity to show it to you here.

A deeper understanding of this code would require more space than we can afford, so we encourage you to read up on **database management systems** (**DBMS**), SQL, relational algebra, and SQLAlchemy.

Now that we have our models, let us use them to persist some data.

Look at the following example (all the snippets presented here, until indicated otherwise, belong to the file `alchemy.py` in the `persistence` folder):

```
# persistence/alchemy.py
from sqlalchemy import create_engine, select, func
from sqlalchemy.orm import Session
from alchemy_models import Person, Email, Base

# swap these lines to work with an actual DB file
# engine = create_engine('sqlite:///example.db')
engine = create_engine("sqlite:///:memory:")
Base.metadata.create_all(engine)
```

First, we import the functions and classes we need. We then proceed to create an engine for the application, and finally, we instruct SQLAlchemy to create all the tables through the given engine.

The `create_engine()` function supports a parameter called `echo`, which can be set to `True`, `False`, or the string `"debug"`, to enable different levels of logging of all statements and the `repr()` of their parameters. Please refer to the official SQLAlchemy documentation for further information.

In SQLAlchemy, an engine is a core component that serves as the primary interface between Python applications and databases. It manages two crucial aspects of database interactions: connections and SQL statement execution.

After the imports and creating the engine and tables, we set up a session via a context manager, using the engine we just created. We start by creating two `Person` objects:

```
with Session(engine) as session:
    anakin = Person(name="Anakin Skywalker", age=32)
    obione = Person(name="Obi-Wan Kenobi", age=40)
```

We then add email addresses to both objects using two different techniques. One assigns them to a list, and the other one simply appends them:

```
    obione.emails = [
        Email(email="obi1@example.com"),
        Email(email="wanwan@example.com"),
    ]

    anakin.emails.append(Email(email="ani@example.com"))
    anakin.emails.append(Email(email="evil.dart@example.com"))
    anakin.emails.append(Email(email="vader@example.com"))
```

We have not touched the database yet. It is only when we use the `session` object that something actually happens in it:

```
    session.add(anakin)
    session.add(obione)
    session.commit()
```

Adding the two `Person` instances is enough to also add their email addresses (this is thanks to the cascading effect). Calling `commit()` causes SQLAlchemy to commit the transaction and save the data in the database.

A **transaction** is an operation that provides something like a sandbox, but in a database context. As long as the transaction hasn't been committed, we can roll back any modification we have done to the database, and by doing so, revert to the state we were in before starting the transaction itself. SQLAlchemy offers more complex and granular ways to deal with transactions, which you can study in its official documentation, as it is quite an advanced topic.

We now query for all the people whose name starts with `Obi` by using `like()`, which hooks to the `LIKE` operator in SQL:

```
    obione = session.scalar(
        select(Person).where(Person.name.like("Obi%"))
```

```
    )
    print(obione, obione.emails)
```

We take the first result of that query (we know we only have Obi-Wan anyway) and print it. We then fetch `anakin` by using an exact match on his name, just to show you another way of filtering:

```
    anakin = session.scalar(
        select(Person).where(Person.name == "Anakin Skywalker")
    )
    print(anakin, anakin.emails)
```

We then capture Anakin's ID, and delete the `anakin` object from the global frame (this does not delete the entry from the database):

```
    anakin_id = anakin.id
    del anakin
```

The reason we do this is because we want to show you how to fetch an object by its ID. To display the full content of the database, we have written a `display_info()` function. It works by fetching the email addresses first and person objects later, through their relationship with `Email`. It also provides a count of all objects per model. In the module, this function is defined before entering the context manager that provides the session:

```
def display_info(session):
    # get all emails first
    emails = select(Email)

    # display results
    print("All emails:")
    for email in session.scalars(emails):
        print(f" - {email.person.name} <{email.email}>")

    # display how many objects we have in total
    people = session.scalar(
        select(func.count()).select_from(Person)
    )
    emails = session.scalar(
        select(func.count()).select_from(Email)
    )
```

```
    print("Summary:")
    print(f" {people=}, {emails=}")
```

We call this function, then we fetch and delete `anakin`. Finally, we display the info again to verify that he has actually disappeared from the database:

```
    display_info(session)

    anakin = session.get(Person, anakin_id)
    session.delete(anakin)
    session.commit()

    display_info(session)
```

The output of all these snippets run together is the following (for your convenience, we have separated the output into four blocks, to reflect the four blocks of code that produce that output):

```
$ python alchemy.py
Obi-Wan Kenobi(id=2) [obi1@example.com, wanwan@example.com]

Anakin Skywalker(id=1) [
    ani@example.com, evil.dart@example.com, vader@example.com
]

All emails:
 - Anakin Skywalker <ani@example.com>
 - Anakin Skywalker <evil.dart@example.com>
 - Anakin Skywalker <vader@example.com>
 - Obi-Wan Kenobi <obi1@example.com>
 - Obi-Wan Kenobi <wanwan@example.com>
Summary:
 people=2, emails=5

All emails:
 - Obi-Wan Kenobi <obi1@example.com>
 - Obi-Wan Kenobi <wanwan@example.com>
Summary:
 people=1, emails=2
```

As you can see from the last two blocks, deleting `anakin` has deleted one `Person` object and the three email addresses associated with it. Again, this is because cascading took place when we deleted `anakin`.

This concludes our brief introduction to data persistence. It is a vast and, at times, complex domain that we encourage you to explore, learning as much theory as possible. Lack of knowledge or proper understanding, when it comes to database systems, can impact the number of bugs in the system, as well as its performance.

Configuration files

Configuration files are crucial components of many Python applications. They allow developers to separate the main application code from settings and parameters. This separation is helpful for maintaining, managing, and distributing software, especially when an application needs to run in different environments – such as development, production, and testing – with different configurations.

Configuration files allow:

- **Flexibility**: Users can change the behavior of an application without modifying its code. This is particularly useful for applications that are deployed across different environments, or require credentials to a database, API keys, and so on.
- **Security**: Sensitive information, like authentication credentials, API keys, or secret tokens, should be kept out of the source code and managed separately from the codebase.

Common formats

Configuration files can be written in several formats, each of which has its own syntax and features. A few popular ones are `INI`, `JSON`, `YAML`, `TOML`, and `.env`.

In this short section, we are going to briefly explore the `INI` and `TOML` formats. In *Chapter 14*, *Introduction to API Development*, we will also use a `.env` file.

The INI configuration format

The `INI` format is a simple text file, divided into sections. Each section contains properties expressed in the form of key/value pairs.

To learn more about this format, please visit `https://en.wikipedia.org/wiki/INI_file`.

Let us look at an example INI configuration file:

```
# config_files/config.ini
[owner]
name = Fabrizio Romano
dob = 1975-12-29T11:50:00Z

[DEFAULT]
title = Config INI example
host = 192.168.1.1

[database]
host = 192.168.1.255
user = redis
password = redis-password
db_range = [0, 32]

[database.primary]
port = 6379
connection_max = 5000

[database.secondary]
port = 6380
connection_max = 4000
```

In the preceding text, there are some sections dedicated to a database connection. Common properties can be found in the `database` section, whereas specific properties are placed in the `.primary` or `.secondary` sections, which represent configurations to connect to a *primary* and *secondary* database, respectively. There is also an `owner` section and a `DEFAULT` section.

To read this configuration in an application, we can use the `configparser` module from the standard library (`https://docs.python.org/3/library/configparser.html`). It is straightforward in that it will produce an object similar to a dictionary, with the added bonus that the `DEFAULT` section automatically provides values for all other sections.

Let us see an example session from the Python shell:

```
# config_files/config-ini.txt
>>> import configparser
```

```
>>> config = configparser.ConfigParser()
>>> config.read("config.ini")
['config.ini']
>>> config.sections()
['owner', 'database', 'database.primary', 'database.secondary']
>>> config.items("database")
[
    ('title', 'Config INI example'), ('host', '192.168.1.255'),
    ('user', 'redis'), ('password', 'redis-password'),
    ('db_range', '[0, 32]')
]
>>> config["database"]
<Section: database>
>>> dict(config["database"])
{
    'host': '192.168.1.255', 'user': 'redis',
    'password': 'redis-password', 'db_range': '[0, 32]',
    'title': 'Config INI example'
}
>>> config["DEFAULT"]["host"]
'192.168.1.1'
>>> dict(config["database.secondary"])
{
    'port': '6380', 'connection_max': '4000',
    'title': 'Config INI example', 'host': '192.168.1.1'
}
>>> config.getint("database.primary", "port")
6379
```

Notice how we import `configparser` and use it to create a `config` object. This object exposes various methods; you can get a list of sections, as well as retrieving any value in it.

Internally, `configparser` stores values as strings, so we need to cast them appropriately, if we want to use them as the Python object they represent. There are some methods on the `ConfigParser` object, namely `getint()`, `getfloat()`, and `getboolean()`, that will retrieve a value and return it cast to the indicated type, but as you can see the list is rather short.

Notice also how properties from the `DEFAULT` section are injected in all other sections. Moreover, when a section defines a key that is also present in the `DEFAULT` section, the value from the original section will not be overwritten by the `DEFAULT` one. You can see an example of this in the highlighted code, which shows that the `title` property is present in the `database` section, and the `host` one, which is present in both sections, retains the value `'192.168.1.255'` correctly.

The TOML configuration format

The `TOML` format is quite popular in Python applications, and it has a richer set of features compared to the INI one. If you wish to learn its syntax, please refer to `https://toml.io/`.

Here, we are going to see a quick example that follows the previous one.

```
# config_file/config.toml
title = "Config Example"

[owner]
name = "Fabrizio Romano"
dob = 1975-12-29T11:50:00Z

[database]
host = "192.168.1.255"
user = "redis"
password = "redis-password"
db_range = [0, 32]

[database.primary]
port = 6379
connection_max = 5000

[database.secondary]
port = 6380
connection_max = 4000
```

This time, we have no `DEFAULT` section, and properties are specified slightly differently, in that strings are surrounded by quotes, while numbers are not.

We will use the `tomllib` module from the standard library (`https://docs.python.org/3/library/tomllib.html`) to read this configuration:

```
# config_files/config-toml.txt
>>> import tomllib
>>> with open("config.toml", "rb") as f:
...     config = tomllib.load(f)
...
>>> config
{
    'title': 'Config Example',
    'owner': {
        'name': 'Fabrizio Romano',
        'dob': datetime.datetime(
            1975, 12, 29, 11, 50, tzinfo=datetime.timezone.utc
        )
    },
    'database': {
        'host': '192.168.1.255',
        'user': 'redis',
        'password': 'redis-password',
        'db_range': [0, 32],
        'primary': {'port': 6379, 'connection_max': 5000},
        'secondary': {'port': 6380, 'connection_max': 4000}
    }
}
>>> config["title"]
'Config Example'
>>> config["owner"]
{
    'name': 'Fabrizio Romano',
    'dob': datetime.datetime(
        1975, 12, 29, 11, 50, tzinfo=datetime.timezone.utc
    )
}
>>> config["database"]["primary"]
{'port': 6379, 'connection_max': 5000}
>>> config["database"]["db_range"]
[0, 32]
```

Notice how, this time, the `config` object is a dictionary. Because of the way we have specified the `database.primary` and `database.secondary` sections, `tomllib` has created a nested structure to represent them.

With TOML, values are correctly cast to Python objects. We have strings, numbers, lists, and even a `datetime` object, created from the iso-formatted string representing Fabrizio's date of birth. On the `tomllib` documentation page, you can find a table with all possible conversions.

Summary

In this chapter, we explored working with files and directories. We learned how to read and write on files, and how to do that elegantly by using context managers. We also explored directories: how to list their content, both recursively and not. We also learned about paths, which are the gateway to accessing both files and directories.

We then briefly saw how to create a ZIP archive and extract its content. The source code of the book also contains an example with a different compression format: `tar.gz`.

We talked about data interchange formats and explored JSON in some depth. We had some fun writing custom encoders and decoders for specific Python data types.

Then, we explored I/O, both with in-memory streams and HTTP requests.

We saw how to persist data using `pickle`, `shelve`, and the SQLAlchemy ORM library.

And finally, we explored two examples of configuration files, using the INI and TOML formats.

You should now have a good understanding of how to deal with files and data persistence, and we hope you will take the time to explore these topics in much more depth by yourself.

The next chapter will look at cryptography and tokens.

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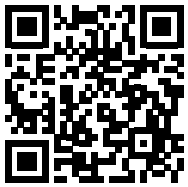
`https://discord.com/invite/uaKmaz7FEC`



9

Cryptography and Tokens

> *"Three may keep a secret, if two of them are dead."*
>
> *– Benjamin Franklin, Poor Richard's Almanack*

In this short chapter, we are going to give you a brief overview of the cryptographic services offered by the Python standard library. We are also going to touch upon JSON Web Tokens, an interesting standard for representing claims securely between two parties.

We are going to explore the following:

- Hashlib
- HMAC
- Secrets
- JSON Web Tokens with PyJWT, which seems to be the most popular Python library for dealing with JWTs

Let us start by taking a moment to talk about cryptography and why it is so important.

The need for cryptography

It is estimated that, as of 2024, there are approximately 5.35 to 5.44 billion people using the internet worldwide. Every year, more people are using online banking services, shopping online, or just talking to friends and family on social media. All these people expect that their money will be safe, their transactions secure, and their conversations private.

Therefore, if you are an application developer, you must take security very seriously. It doesn't matter how small or insignificant your application is: security should always be a concern for you.

Security in information technology is achieved by employing several different means, but by far the most important one is cryptography. Almost everything you do with your computer or phone should include a layer where cryptography takes place. For example, cryptography is used to secure online payments, to transfer messages over a network in such a way that even if someone intercepts them, they will not be able to read them, and to encrypt your files when you back them up in the cloud.

The purpose of this chapter is not to teach you all the intricacies of cryptography—there are entire books dedicated to the subject. Instead, we will show you how you can use the tools that Python offers you to create digests, tokens, and, in general, to be on the safe(r) side when you need to implement something cryptography-related. As you read this chapter, it is worth bearing in mind that there is much more to cryptography than just encrypting and decrypting data; in fact, you will not find any examples of encryption or decryption in the entire chapter!

Useful guidelines

Always remember the following rule: do not attempt to create your own hash or encryption functions. Simply don't. Use tools and functions that are there already. It is incredibly tough to invent a good, solid, robust algorithm to do hashing or encryption, so it is best to leave it to professional cryptographers.

It is important to understand cryptography, so try and learn as much as you can about this subject. There is plenty of information on the web, but for your convenience, we will put some useful references at the end of this chapter.

Now, let us dig into the first of the standard library modules we want to show you: `hashlib`.

Hashlib

This module provides access to a variety of cryptographic hash algorithms. These are mathematical functions that take a message of any size and produce a fixed-size result, which is referred to as a **hash** or **digest**. Cryptographic hashes have many uses, from verifying data integrity to securely storing and verifying passwords.

Ideally, cryptographic hash algorithms should be:

- **Deterministic**: The same message should always produce the same hash.

- **Irreversible**: It should not be feasible to determine the original message from the hash.
- **Collision resistant**: It should be difficult to find two different messages that produce the same hash.

These properties are crucial for the secure application of hashes. For example, it is considered imperative that passwords are only stored in hashed form.

The irreversibility property ensures that even if a data breach occurs and an attacker gets hold of a password database, it would not be feasible for them to obtain the original passwords. Having the passwords stored only as hashes means that the only way to verify a user's password when they log in is to compute the hash of the password they provided and compare it against the stored hash. Of course, this will not work if the hash algorithm is not deterministic.

Collision resistance is also important. It ensures data integrity in that if a hash is used to provide a fingerprint for data, it is crucial that when the data changes, the fingerprint changes too. Collision resistance prevents an attacker from replacing a document with a different one that has the same hash. Moreover, many security protocols rely on the uniqueness guaranteed by collision-resistant hash functions.

The exact set of algorithms that are available through `hashlib` vary depending on the underlying libraries used on your platform. Some algorithms, however, are guaranteed to be present in all systems. Let us see how to find out what is available (note that your results might be different from ours):

```
# hlib.txt
>>> import hashlib
>>> hashlib.algorithms_available
{'sha3_256', 'sha224', 'blake2b', 'sha512_224', 'ripemd160',
 'sha1', 'sha512_256', 'sha3_512', 'sha512', 'sha384', 'sha3_384',
'sha3_224', 'shake_256', 'shake_128', 'sm3', 'md5-sha1', 'sha256',
'md5', 'blake2s'}
>>> hashlib.algorithms_guaranteed
{'sha512', 'sha3_256', 'shake_128', 'sha224', 'blake2b',
 'shake_256', 'sha384', 'sha1', 'sha3_512', 'sha3_384', 'sha256',
 'sha3_224', 'md5', 'blake2s'}
```

By opening a Python shell, we can get the set of available algorithms for our system. If our application talks to third-party applications, it is always best to pick an algorithm out of the guaranteed set, as that means every platform supports them. Notice that a lot of them start with *sha*, which stands for *secure hash algorithm*.

Let us keep going in the same shell; we are going to create a hash for the byte string `b"Hash me now!"`:

```
>>> h = hashlib.blake2b()
>>> h.update(b"Hash me")
>>> h.update(b" now!")
>>> h.hexdigest()
'56441b566db9aafcf8cdad3a4729fa4b2bfaab0ada36155ece29f52ff70e1e9d'
'7f54cacfe44bc97c7e904cf79944357d023877929430bc58eb2dae168e73cedf'
>>> h.digest()
b'VD\x1bVm\xb9\xaa\xfc\xf8\xcd\xad:G)\xfaK+\xfa\xab\n\xda6\x15^'
b'\xce)\xf5/\xf7\x0e\x1e\x9d\x7fT\xca\xcf\xe4K\xc9|~\x90L\xf7'
b'\x99D5}\x028w\x92\x940\xbcX\xeb-\xae\x16\x8es\xce\xdf'
>>> h.block_size
128
>>> h.digest_size
64
>>> h.name
'blake2b'
```

Here, we have used the `blake2b()` cryptographic function, which is quite sophisticated and was added in Python 3.6. After creating the hash object, `h`, we update its message in two steps. Not that we needed to, but sometimes we need to hash data that is not available all at once, so it is good to know we can do it in steps.

Once we have added the entire message, we get the hexadecimal representation of the digest. This will use two characters per byte (as each character represents four bits, which is half a byte). We also get the byte representation of the digest, and then we inspect its details: it has a block size (the internal block size of the hash algorithm in bytes) of 128 bytes, a digest size (the size of the resulting hash in bytes) of 64 bytes, and a name.

Let us see what we get if, instead of the `blake2b()` function, we use `sha512()`:

```
>>> hashlib.sha512(b"Hash me too!").hexdigest()
'a0d169ac9487fc6c78c7db64b54aefd01bd245bbd1b90b6fe5648c3c4eb0ea7d'
'93e1be50127164f21bc8ddb3dd45a6b4306dfe9209f2677518259502fed27686'
```

The resulting hash is as long as the `blake2b` one. Notice that we can construct the hash object with the message and compute the digest in one line.

Hashing is an interesting topic, and of course, the simple examples we have seen so far are just the start. The `blake2b()` function allows us a great deal of flexibility thanks to a number of parameters that can be adjusted. This means that it can be adapted for different applications or adjusted to protect against particular types of attacks.

Here, we will just briefly discuss one of these parameters; for the full details, please refer to the official documentation at `https://docs.python.org/3/library/hashlib.html`. The `person` parameter is quite interesting. It is used to *personalize* the hash, forcing it to produce different digests for the same message. This can help to improve security when the same hash function is used for different purposes within the same application:

```
>>> import hashlib
>>> h1 = hashlib.blake2b(
...     b"Important data", digest_size=16, person=b"part-1")
>>> h2 = hashlib.blake2b(
...     b"Important data", digest_size=16, person=b"part-2")
>>> h3 = hashlib.blake2b(
...     b"Important data", digest_size=16)
>>> h1.hexdigest()
'c06b9af95d5aa6307e7e3fd025a15646'
>>> h2.hexdigest()
'9cb03be8f3114d0f06bddaedce2079c4'
>>> h3.hexdigest()
'7d35308ca3b042b5184728d2b1283d0d'
```

Here, we have also used the `digest_size` parameter to get hashes that are only 16 bytes long.

General-purpose hash functions, like `blake2b()` or `sha512()`, are not suitable for securely storing passwords. General-purpose hash functions are quite fast to compute on modern computers, which makes it feasible for an attacker to reverse the hash by **brute force** (trying millions of possibilities per second until they find a match). Key derivation algorithms like `pbkdf2_hmac()` are designed to be slow enough to make such brute-force attacks infeasible. The `pbkdf2_hmac()` key derivation algorithm achieves this by using many repeated applications of a general-purpose hash function (the number of iterations can be specified as a parameter). As computers get more powerful, it is important to increase the number of iterations we do over time; otherwise, the likelihood of a successful brute-force attack on our data increases as time passes.

Good password hash functions should also use **salt**. Salt is a random piece of data used to initialize the hash function; this randomizes the output of the algorithm and protects against attacks where hashes are compared to tables of known hashes. The `pbkdf2_hmac()` function supports salting via a required `salt` parameter.

Here's how you can use `pbkdf2_hmac()` to hash a password:

```
>>> import os
>>> dk = hashlib.pbkdf2_hmac("sha256", b"password123",
...     salt=os.urandom(16), iterations=200000)
>>> dk.hex()
'ac34579350cf6d05e01e745eb403fc50ac0e62fbeb553cbb895e834a77c37aed'
```

Notice that we have used `os.urandom()` to provide a 16-byte random salt, as recommended by the documentation.

Normally, the value of the salt is stored alongside the hash. When a user attempts to log in, your program uses the stored salt to create the hash of the given password, which is then compared to the stored hash. Using the same value for the salt ensures that the hash will be the same when the password is correct.

We encourage you to explore and experiment with this module, as eventually, you will have to use it. Now, let us move on to the `hmac` module.

HMAC

This module implements the **HMAC** algorithm, as described by RFC 2104 (`https://datatracker.ietf.org/doc/html/rfc2104.html`). HMAC (which stands for **hash-based message authentication code** or **keyed-hash message authentication code**, depending on who you ask) is a widely used mechanism for authenticating messages and verifying that they have not been tampered with.

The algorithm combines a message with a secret key and generates a hash of the combination. This hash is referred to as a **message authentication code** (**MAC**) or **signature**. The signature is stored or transmitted along with the message. You can verify that the message has not been tampered with by re-computing the signature using the same secret key and comparing it to the previously computed signature. The secret key must be carefully protected; otherwise, an attacker with access to the key would be able to modify the message and replace the signature, thereby defeating the authentication mechanism.

Let us see a small example of how to compute a MAC:

```
# hmc.py
import hmac
import hashlib

def calc_digest(key, message):
    key = bytes(key, "utf-8")
    message = bytes(message, "utf-8")
    dig = hmac.new(key, message, hashlib.sha256)
    return dig.hexdigest()

mac = calc_digest("secret-key", "Important Message")
```

The `hmac.new()` function takes a secret key, a message, and the hash algorithm to use. It returns an `hmac` object, which has a similar interface to the hash objects from `hashlib`. The key must be a `bytes` or `bytearray` object and the message can be any `bytes`-like object. Therefore, we convert our `key` and the `message` into bytes before creating an `hmac` instance (`dig`), which we use to get a hexadecimal representation of the hash.

We will see a bit more of how HMAC signatures can be used later in this chapter when we talk about JWTs. Before that, however, we will take a quick look at the `secrets` module.

Secrets

This small module was added in Python 3.6 and deals with three things: random numbers, tokens, and digest comparison. It uses the most secure random number generators provided by the underlying operating system to generate tokens and random numbers suitable for use in cryptographic applications. Let us have a quick look at what it provides.

Random objects

We can use three functions to produce random objects:

```
# secrs/secr_rand.py
import secrets

print(secrets.choice("Choose one of these words".split()))
print(secrets.randbelow(10**6))
print(secrets.randbits(32))
```

The first one, `choice()`, returns an element at random from a non-empty sequence. The second, `randbelow()`, generates a random integer between 0 and the argument you call it with, and the third, `randbits()`, generates an integer with the given number of random bits in it. Running that code produces the following output (which will, of course, be different every time it is run):

```
$ python secr_rand.py
one
133025
1509555468
```

You should use these functions instead of those from the `random` module whenever you need randomness in the context of cryptography, as these are specially designed for this task. Let us see what the module provides for tokens.

Token generation

Again, we have three functions for generating tokens, each in a different format. Let us see the example:

```
# secrs/secr_rand.py
import secrets

print(secrets.token_bytes(16))
print(secrets.token_hex(32))
print(secrets.token_urlsafe(32))
```

The `token_bytes()` function simply returns a random byte string containing the specified number of bytes (16, in this example). The other two do the same, but `token_hex()` returns a token in hexadecimal format, and `token_urlsafe()` returns a token that only contains characters suitable for being included in a URL. Here is the output (which is a continuation of the previous run):

```
b'\x0f\x8b\x8f\x0f\xe3\xceJ\xbc\x18\xf2\x1e\xe0i\xee1\x99'
98e80cddf6c3718113180456723 99b0950b8e3207d18b50d99d724d31d17f0a7
63eNkRalj8dgZqmkezjbEYoGddVcutgvwJthSLf5kho
```

Let us see how we can use these tools to write our own random password generator:

```
# secrs/secr_gen.py
import secrets
from string import digits, ascii_letters
```

```
def generate_pwd(length=8):
    chars = digits + ascii_letters
    return "".join(secrets.choice(chars) for c in range(length))

def generate_secure_pwd(length=16, upper=3, digits=3):
    if length < upper + digits + 1:
        raise ValueError("Nice try!")
    while True:
        pwd = generate_pwd(length)
        if (
            any(c.islower() for c in pwd)
            and sum(c.isupper() for c in pwd) >= upper
            and sum(c.isdigit() for c in pwd) >= digits
        ):
            return pwd

print(generate_secure_pwd())
print(generate_secure_pwd(length=3, upper=1, digits=1))
```

The `generate_pwd()` function simply generates a random string of a given length by joining together `length` characters, picked at random from a string that contains all the letters of the alphabet (lowercase and uppercase), and the 10 decimal digits.

Then, we define another function, `generate_secure_pwd()`, that simply keeps calling `generate_pwd()` until the random string we get matches some basic requirements. The password must be `length` characters long, have at least one lowercase character, `upper` uppercase characters, and `digits` digits.

If the total number of uppercase characters, lowercase characters, and digits specified by the parameters is greater than the length of the password we are generating, we can never satisfy the conditions. We check for this before starting the loop and raise a `ValueError` if the given parameters would result in an infinite loop.

The body of the `while` loop is straightforward: first, we generate the random password, and then we verify the conditions by using `any()` and `sum()`. The `any()` function returns `True` if any of the items in the iterable it is called with evaluate to `True`. The use of `sum()` is actually slightly trickier here, in that it exploits **polymorphism**. As you may recall from *Chapter 2*, *Built-In Data Types*, the `bool` type is a subclass of `int`, therefore when summing on an iterable of `True` and `False` values, they will automatically be interpreted as integers (with the values 1 and 0) by the `sum()` function.

This is an example of polymorphism, which we briefly discussed in *Chapter 6, OOP, Decorators, and Iterators*.

Running the example produces the following result:

```
$ python secr_gen.py
mgQ3Hj57KjD1LI7M
b8G
```

Of course, you wouldn't want to use a password of length 3.

One common use of random tokens is in password reset URLs for websites. Here is an example of how we can generate such a URL:

```
# secrs/secr_reset.py
import secrets

def get_reset_pwd_url(token_length=16):
    token = secrets.token_urlsafe(token_length)
    return f"https://example.com/reset-pwd/{token}"

print(get_reset_pwd_url())
```

Running the above produced this output:

```
$ python secr_reset.py
https://example.com/reset-pwd/ML_6_2wxDpXmDJLHrDnrRA
```

Digest comparison

This is probably quite surprising, but the `secrets` module also provides a `compare_digest(a, b)` function, which is the equivalent of comparing two digests by simply doing `a == b`. So, why would we need that function? It is because it has been designed to prevent timing attacks. These kinds of attacks can infer information about where the two digests start being different, according to the time it takes for the comparison to fail. So, `compare_digest()` prevents this attack by removing the correlation between time and failures. We think this is a brilliant example of how sophisticated attacking methods can be. If you raised your eyebrows in astonishment, maybe now it is clearer why we said never to implement cryptography functions by yourself.

This brings us to the end of our tour of the cryptographic services in the Python standard library. Now, let us move on to a different type of token: JWTs.

JSON Web Tokens

JSON Web Token, or **JWT**, is a JSON-based open standard for creating tokens that assert a number of **claims**. JWTs are frequently used as authentication tokens. In this context, the claims typically are statements about the identity and permissions of an authenticated user. The tokens are cryptographically signed, which makes it possible to verify that the content of the token has not been modified since it was issued. You can learn all about this technology on the website (`https://jwt.io`).

This type of token consists of three sections, joined together by dots, in the format *A.B.C*. *B* is the payload, which is where we put the claims. *C* is the signature, which is used to verify the validity of the token, and *A* is a header, which identifies the token as a JWT, and indicates the algorithm used to compute the signature. *A*, *B*, and *C* are all encoded with a URL-safe Base64 encoding (which we will refer to as Base64URL). The Base64URL encoding makes it possible to use JWTs as part of URLs (typically as query parameters); however, JWTs do also appear in other places, including HTTP headers.

`Base64` is a popular binary-to-text encoding scheme that represents binary data in an ASCII string format by translating it into a Radix-64 representation. The Radix-64 representation uses the letters A-Z, a-z, and the digits 0-9, plus the two symbols + and /, giving a total of 64 symbols. `Base64` is used, for example, to encode images attached to an email. It happens seamlessly, so the vast majority of users are completely oblivious to this fact. `Base64URL` is a variant of `Base64` encoding where the + and / characters (which have specific meanings in the context of a URL) are replaced with - and _. The = character (which is used for padding in `Base64`) also has a special meaning within URLs and is omitted in `Base64URL`.

The way this type of token works is slightly different from what we have seen so far in this chapter. In fact, the information that the token carries is always visible. You just need to decode *A* and *B* from Base64URL to get the algorithm and the payload. The security lies in part *C*, which is an HMAC signature of the header and payload. If you try to modify either the *A* or *B* part by editing the header or the payload, encoding it back to Base64URL, and replacing it in the token, the signature will not match, and therefore the token will be invalid.

This means that we can build a payload with claims such as *logged in as admin*, or something along those lines, and as long as the token is valid, we know we can trust that that user is logged in as an admin.

When dealing with JWTs, you want to make sure you have researched how to handle them safely. Things like not accepting unsigned tokens or restricting the list of algorithms you use to encode and decode, as well as other security measures, are very important and you should take the time to investigate and learn them.

For this part of the code, you will have to have the `PyJWT` and `cryptography` Python packages installed. As always, you will find them in the requirements of the source code for this chapter.

Let us start with a simple example:

```
# jwt/tok.py
import jwt

data = {"payload": "data", "id": 123456789}
algs = ["HS256", "HS512"]

token = jwt.encode(data, "secret-key")
data_out = jwt.decode(token, "secret-key", algorithms=algs)
print(token)
print(data_out)
```

We define the `data` payload, which contains an ID and some payload data. We create a token using the `jwt.encode()` function, which takes the payload and a secret key. The secret key is used to generate the HMAC signature of the token header and payload. Next, we decode the token again, specifying the signature algorithms that we are willing to accept. The default algorithm used to calculate the token is `HS256`; in this example, we accept either `HS256` or `HS512` when decoding (if the token had been generated using a different algorithm, it would be rejected with an exception). Here is the output:

```
$ python jwt/tok.py
eyJhbGciOiJIUzI1NiIsInR5cCI6IkpXVCJ9.eyJwYXlsb2FkIjoiZGF0YSIsIm...
{'payload': 'data', 'id': 123456789}
```

As you can see, the token is a binary string of Base64URL-encoded pieces of data (abridged to fit on one line). We called `jwt.decode()`, providing the correct secret key. If we had supplied the wrong key, we would have gotten an error, since the signature can only be verified with the same secret that was used to generate it.

JWTs are often used to transmit information between two parties. For example, authentication protocols that allow websites to rely on third-party identity providers to authenticate users often use JWTs. In such cases, the secret key used to sign tokens needs to be shared between the two parties. Therefore, it is often referred to as a **shared secret**.

Care must be taken to protect the shared secret since anyone with access to it can generate valid tokens.

Sometimes, you might want to be able to inspect the content of the token without verifying the signature first. You can do so by simply calling `decode()` this way:

```
# jwt/tok.py
jwt.decode(token, options={"verify_signature": False})
```

This is useful, for example, when values in the token payload are needed to recover the secret key, but that technique is quite advanced so we will not be spending time on it in this context. Instead, let us see how we can specify a different algorithm for computing the signature:

```
# jwt/tok.py
token512 = jwt.encode(data, "secret-key", algorithm="HS512")
data_out = jwt.decode(
    token512, "secret-key", algorithms=["HS512"]
)
print(data_out)
```

Here, we have used the `HS512` algorithm to generate the token and, on decoding, specified that we would only accept tokens generated using the `HS512` algorithm. The output is the original payload dictionary.

Now, while you are free to put whatever you want in the token payload, there are some claims that have been standardized; they are essential for ensuring security, consistency, and interoperability across different systems and applications.

Registered claims

The JWT standard defines the following official **registered claims**:

- `iss`: The issuer of the token
- `sub`: The subject information about the party this token is carrying information about

- `aud`: The audience for the token
- `exp`: The expiration time, after which the token is invalid
- `nbf`: The not before (time), or the time before which the token is not considered to be valid yet
- `iat`: The time at which the token was issued
- `jti`: The token ID

Claims that are not defined in the standard can be categorized as public or private:

- **Public**: Claims that are publicly allocated for a particular purpose. Public claim names can be reserved by registering them with the IANA JSON Web Token Claims Registry. Alternatively, the claims should be named in a way that ensures that they do not clash with any other public or official claim names (one way of achieving this could be to prepend a registered domain name to the claim name).
- **Private**: Any other claims that do not fall under the above category are referred to as private claims. The meaning of such claims is typically defined within the context of a particular application, and they are meaningless outside that context. To prevent ambiguity and confusion, care must be taken to avoid name clashes.

To learn about claims, please refer to the official website. Now, let us see a couple of code examples involving a subset of these claims.

Time-related claims

This is how we might use the claims related to time:

```
# jwt/claims_time.py
from datetime import datetime, timedelta, UTC
from time import sleep, time
import jwt

iat = datetime.now(tz=UTC)
nfb = iat + timedelta(seconds=1)
exp = iat + timedelta(seconds=3)

data = {"payload": "data", "nbf": nfb, "exp": exp, "iat": iat}

def decode(token, secret):
    print(f"{time():.2f}")
    try:
```

```
        print(jwt.decode(token, secret, algorithms=["HS256"]))
    except (
        jwt.ImmatureSignatureError,
        jwt.ExpiredSignatureError,
    ) as err:
        print(err)
        print(type(err))

secret = "secret-key"
token = jwt.encode(data, secret)

decode(token, secret)
sleep(2)
decode(token, secret)
sleep(2)
decode(token, secret)
```

In this example, we set the issued at (`iat`) claim to the current UTC time (**UTC** stands for **Co-ordinated Universal Time**). We then set the "not before" (`nbf`) and "expire time" (`exp`) claims to 1 and 3 seconds from now, respectively. We define a `decode()` helper function that reacts to a token not being valid yet, or being expired, by trapping the appropriate exceptions, and then we call it three times, interspersed by two calls to `sleep()`.

This way, we will try to decode the token before it is valid, then when it is valid, and finally, after it has expired. This function also prints a useful timestamp before attempting to decode the token. Let us see how it goes (blank lines have been added for readability):

```
$ python jwt/claims_time.py
1716674892.39
The token is not yet valid (nbf)
<class 'jwt.exceptions.ImmatureSignatureError'>

1716674894.39
{'payload': 'data', 'nbf': 1716674893, 'exp': 1716674895, 'iat':
1716674892}

1716674896.39
Signature has expired
<class 'jwt.exceptions.ExpiredSignatureError'>
```

As you can see, it executed as expected. We get descriptive messages from the exceptions and get the original payload back when the token is valid.

Authentication-related claims

Here we have another quick example, this time, involving the issuer (`iss`) and audience (`aud`) claims. The code is conceptually very similar to the previous example, and we are going to exercise it in the same way:

```
# jwt/claims_auth.py
import jwt

data = {"payload": "data", "iss": "hein", "aud": "learn-python"}
secret = "secret-key"
token = jwt.encode(data, secret)

def decode(token, secret, issuer=None, audience=None):
    try:
        print(
            jwt.decode(
                token,
                secret,
                issuer=issuer,
                audience=audience,
                algorithms=["HS256"],
            )
        )
    except (
        jwt.InvalidIssuerError,
        jwt.InvalidAudienceError,
    ) as err:
        print(err)
        print(type(err))

# Not providing both the audience and issuer will fail
decode(token, secret)

# Not providing the issuer will succeed
decode(token, secret, audience="learn-python")
```

```
# Not providing the audience will fail
decode(token, secret, issuer="hein")

# Both will fail
decode(token, secret, issuer="wrong", audience="learn-python")
decode(token, secret, issuer="hein", audience="wrong")

# This will succeed
decode(token, secret, issuer="hein", audience="learn-python")
```

As you can see, this time, we specified both issuer (`iss`) and audience (`aud`) when creating the token. Decoding this token succeeds even if we omit the `issuer` argument to `jwt.decode()`. However, if the `issuer` is provided but does not match the iss field in the token, decoding fails. On the other hand, if the `audience` argument is omitted or does not match the `aud` field in the token, `jwt.decode()` will fail.

As in the previous example, we have written a custom `decode()` function that reacts to the appropriate exceptions. See if you can follow along with the calls and the relative output that follows (we will help with some blank lines):

```
$ python jwt/claims_time.py
Invalid audience
<class 'jwt.exceptions.InvalidAudienceError'>

{'payload': 'data', 'iss': 'hein', 'aud': 'learn-python'}

Invalid audience
<class 'jwt.exceptions.InvalidAudienceError'>

Invalid issuer
<class 'jwt.exceptions.InvalidIssuerError'>

Audience doesn't match
<class 'jwt.exceptions.InvalidAudienceError'>

{'payload': 'data', 'iss': 'hein', 'aud': 'learn-python'}
```

Note that, in this example, we varied the arguments to `jwt.decode()` to show you the behavior in various scenarios. In real-world usage, however, you would typically use fixed values for both `audience` and `issuer` and reject any tokens that cannot be decoded successfully. Omitting the `issuer` when decoding means you will accept tokens from any issuer. Omitting the `audience` means you will only accept tokens that do not specify an audience.

Now, let us see one final example for a more complex use case.

Using asymmetric (public key) algorithms

Sometimes, using a shared secret is not the best option. In such cases, it is possible to use an asymmetric key pair instead of HMAC to generate the JWT signature. In this example, we are going to create a token (and decode it) using an **RSA** key pair.

Public key cryptography, or asymmetrical cryptography, is any cryptographic system that uses pairs of keys: public keys, which may be disseminated widely, and private keys, which are known only to the owner. If you are interested in learning more about this topic, please see the end of this chapter for recommendations. A signature can be generated using the private key, and the public key can be used to verify the signature. Thus, two parties can exchange JWTs and the signatures can be verified without any need for a shared secret.

First, let us create an RSA key pair. We are going to use the `ssh-keygen` utility from OpenSSH (`https://www.ssh.com/academy/ssh/keygen`) to do this. In the folder where our scripts for this chapter are, we created a `jwt/rsa` subfolder. Within it, run the following:

```
$ ssh-keygen -t rsa -m PEM
```

Give the name `key` when asked for a filename (it will be saved in the current folder), and simply hit the *Enter* key when asked for a passphrase.

Having generated our keys, we can now change back to the `ch09` folder and run this code:

```
# jwt/token_rsa.py
import jwt

data = {"payload": "data"}

def encode(data, priv_filename, algorithm="RS256"):
    with open(priv_filename, "rb") as key:
        private_key = key.read()
    return jwt.encode(data, private_key, algorithm=algorithm)
```

```
def decode(data, pub_filename, algorithm="RS256"):
    with open(pub_filename, "rb") as key:
        public_key = key.read()
    return jwt.decode(data, public_key, algorithms=[algorithm])

token = encode(data, "jwt/rsa/key")
data_out = decode(token, "jwt/rsa/key.pub")
print(data_out)  # {'payload': 'data'}
```

In this example, we defined a couple of custom functions to encode and decode tokens using private/public keys. As you can see in the `encode()` function, we are using the `RS256` algorithm this time. Notice that when we encode, we provide the private key, which is used to generate the JWT signature. When we decode the JWT, we instead supply the public key, which is used to verify the signature.

The logic is straightforward, and we would encourage you to think about at least one use case where this technique might be more suitable than using a shared key.

Useful references

Here, you can find a list of useful references if you want to dig deeper into the fascinating world of cryptography:

- Cryptography: `https://en.wikipedia.org/wiki/Cryptography`
- JSON Web Tokens: `https://jwt.io`
- RFC standard for JSON Web Tokens: `https://datatracker.ietf.org/doc/html/rfc7519`
- Hash functions: `https://en.wikipedia.org/wiki/Cryptographic_hash_function`
- HMAC: `https://en.wikipedia.org/wiki/HMAC`
- Cryptography services (Python STD library): `https://docs.python.org/3/library/crypto.html`
- IANA JSON Web Token Claims Registry: `https://www.iana.org/assignments/jwt/jwt.xhtml`
- PyJWT library: `https://pyjwt.readthedocs.io/`
- Cryptography library: `https://cryptography.io/`

There is a lot of information on the web and plenty of books you can study, but we would recommend that you start with the main concepts and then gradually dive into the specifics you want to understand more thoroughly.

Summary

In this short chapter, we explored the world of cryptography in the Python standard library. We learned how to create a hash (or digest) for a message using different cryptographic functions. We also learned how to create tokens and deal with random data in the context of cryptography.

We then took a small tour outside the standard library to learn about JSON Web Tokens, which are commonly used in authentication and claims-related functionalities by modern systems and applications.

The most important thing is to understand that doing things manually can be very risky when it comes to cryptography, so it is always best to leave it to the professionals and simply use the tools we have available.

The next chapter will be about testing our code so that we can be confident that it works the way it is supposed to.

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10

Testing

> *"Just as the wise accepts gold after testing it by heating, cutting, and rubbing it, so are my words to be accepted after examining them, but not out of respect for me."*
>
> *– Buddha*

We love this quote by the Buddha. Within the software world, it translates perfectly into the healthy habit of never trusting code just because someone smart wrote it or because it has been working fine for a long time. If it has not been tested, the code is not to be trusted.

Why are tests so important? Well, for one, they give you predictability. Or, at least, they help you achieve high predictability. Unfortunately, there is always some bug that sneaks into the code. But we want our code to be as predictable as possible. What we do not want is to have a surprise; in other words, our code behaving in an unpredictable way. Unpredictability in software that checks the sensors of a plane, a train, or a nuclear power plant can lead to disastrous situations.

We need to test our code; we need to check that its behavior is correct, that it works as expected when it deals with edge cases, that it does not hang when the components it is talking to are broken or unreachable, that the performance is well within the acceptable range, and so on.

This chapter is all about that—making sure that your code is prepared to face the scary outside world, that it is fast enough, and that it can deal with unexpected or exceptional conditions.

In this chapter, we are going to explore the following topics:

- General testing guidelines

- Unit testing
- A brief mention of **test-driven development** (**TDD**)

Let us start by understanding what testing is.

Testing your application

There are many kinds of tests; so many, in fact, that companies often have a dedicated department, called **quality assurance** (**QA**), made up of individuals whose job is to test the software the company developers produce.

To start making an initial classification, we can divide tests into two broad categories: **white-box** and **black-box** tests.

White-box tests are those that exercise the internals of the code; they inspect it down to a fine level of detail. On the other hand, black-box tests are those that consider the software under test as if within a box, the internals of which are ignored. Even the technology, or the language used inside the box, is not important for black-box tests. What they do is plug some input into one end of the box and verify the output at the other end—that's it.

There is also an in-between category called **gray-box** testing, which involves testing a system in the same way we do with the black-box approach, but having some knowledge about the algorithms and data structures used to write the software and only partial access to its source code.

There are many kinds of tests in these categories, each of which serves a different purpose. To give you an idea, here are a few:

- **Frontend tests**: They make sure that the client side of your application is exposing the information that it should, all the links, the buttons, the advertising, and everything that needs to be shown to the client. They may also verify that it is possible to walk a certain path through the **user interface** (**UI**).
- **Scenario tests**: They make use of stories (or scenarios) that help the tester work through a complex problem or test a part of the system.
- **Integration tests**: They verify the behavior of the various components of your application when they are working together and sending messages through interfaces.

- **Smoke tests**: Particularly useful when you deploy a new update on your application, they check whether the most essential, vital parts of your application are still working as they should and that they are not *on fire*. This term comes from when engineers tested circuits by making sure nothing was smoking.
- **Acceptance tests**, or **user acceptance testing (UAT)**: What a developer does with a product owner (for example, in a SCRUM environment) to determine whether the work that was commissioned was carried out correctly.
- **Functional tests**: They verify the features or functionalities of your software.
- **Destructive tests**: They take down parts of your system, simulating a failure, to establish how well the remaining parts of the system perform. This kind of test is performed extensively by companies that need to provide a highly reliable service.
- **Performance tests**: They aim to verify how well the system performs under a specific load of data or traffic so that, for example, engineers can get a better understanding of the bottlenecks in the system that could bring it to its knees in a heavy-load situation, or those that prevent scalability.
- **Usability tests**, and the closely related **user experience (UX) tests**: They aim to check whether the UI is simple and easy to understand and use. They also aim to provide input to the designers so that the UX is improved.
- **Security and penetration tests**: They aim to verify how well the system is protected against attacks and intrusions.
- **Unit tests**: They help the developer write the code in a robust and consistent way, providing the first line of feedback and defense against coding mistakes, refactoring mistakes, and so on.
- **Regression tests**: They provide the developer with useful information about a feature being compromised in the system after an update. Some of the causes for a system being said to have a regression are an old bug resurfacing, an existing feature being compromised, or a new issue being introduced.

Many books and articles have been written about testing, and we have to point you to those resources if you are interested in finding out more about all the different kinds of tests. In this chapter, we will concentrate on unit tests, since they are the backbone of software crafting and form the vast majority of tests that are written by a developer.

Testing is an *art*, an art that you do not learn from books, unfortunately. You can learn all the definitions (and you should) and try to collect as much knowledge about testing as you can, but you will likely be able to test your software properly only when you have accumulated enough experience.

When you are having trouble refactoring a bit of code because every little thing you touch makes a test blow up, you learn how to write less rigid and limiting tests that still verify the correctness of your code but, at the same time, allow you the freedom and joy to play with it, to shape it as you want.

When you are being called too often to fix unexpected bugs in your code, you learn how to write tests more thoroughly, how to come up with a more comprehensive list of edge cases, and strategies to cope with them before they turn into bugs.

When you are spending too much time reading tests and trying to refactor them to change a small feature in the code, you learn to write simpler, shorter, and better-focused tests.

We could go on with this *when you... you learn...*, but we guess you get the picture. You need to apply yourself and build experience. Our suggestion? Study the theory as much as you can, and then experiment using different approaches. Also, try to learn from experienced coders; it is very effective.

Ideally, the more experienced you become, the more you should feel that source code and unit tests are not two separate things. Tests are not optional. They are intimately connected to the code. Source code and unit tests mutually influence each other.

The anatomy of a test

Before we concentrate on unit tests, let us see what a test is, and what its purpose is.

A **test** is a piece of code whose purpose is to verify something in our system. It may be that we are calling a function passing two integers, that an object has a property called `donald_duck`, or that when you place an order on some **application programming interface** (**API**), after a minute you can see it dissected into its basic elements in the database.

A test is typically composed of three sections:

1. **Preparation**: This is where we set up the scene. We prepare all the data, the objects, and the services we need in the places we need them so that they are ready to be used.
2. **Execution**: This is where we execute the bit of logic that is under testing. We perform an action using the data and the interfaces we set up in the preparation phase.

3. **Verification**: This is where we verify the results and make sure they are according to our expectations. We check the returned value of a function, or that some data is in the database, some is not, some has changed, an HTTP request has been made, something has happened, a method has been called, and so on.

While tests usually follow this structure, in a test suite, you will typically find some other constructs that take part in the testing process:

- **Setup**: This is something quite commonly found in several tests. It is logic that can be customized to run for every test, class, module, or even for a whole session. In this phase, developers usually set up connections to databases, populate them with data that will be needed there for the test to make sense, and so on.
- **Teardown**: This is the opposite of the setup; the teardown phase takes place after the tests have run. Like the setup, it can be customized to run for every test, class, module, or session. Typically, in this phase, we destroy any artifacts that were created for the test suite and clean up after ourselves. This is important because we do not want to have any lingering objects around and because it helps to make sure that each test starts from a clean slate.
- **Fixtures**: These are pieces of data used in the tests. By using a specific set of fixtures, outcomes are predictable and therefore tests can perform verifications against them.

In this chapter, we will use the `pytest` Python library. It is a powerful tool that makes testing easier than it would be if we only used standard library tools. `pytest` provides plenty of helpers so that the test logic can focus more on the actual testing than the wiring and boilerplate around it. You will see, when we get to the code, that one of the characteristics of `pytest` is that fixtures, setup, and teardown often blend into one.

Testing guidelines

Like software, tests can be good or bad, with a whole range of shades in the middle. To write good tests, here are some guidelines:

- **Keep them as simple as possible**: It is okay to violate some good coding rules, such as hardcoding values or duplicating code. Tests need, first and foremost, to be as readable as possible and easy to understand. When tests are hard to read or understand, we can never be confident they are actually making sure our code is performing correctly.
- **Tests should verify one thing and one thing only**: It is important that we keep them short and contained. It is perfectly fine to write multiple tests to exercise a single object or function. We just need to make sure that each test has one and only one purpose.

- **Tests should not make any unnecessary assumptions**: This may be tricky to understand at first, but it is important. Verifying that the result of a function call is `[1, 2, 3]` is not the same as saying the output is a list that contains the numbers 1, 2, and 3. In the former, we are also assuming the ordering; in the latter, we are only assuming which items are in the list. The differences sometimes are quite subtle, but they are still important.
- **Tests should exercise the "what," rather than the "how"**: Tests should focus on checking *what* a function is supposed to do, rather than *how* it is doing it. For example, focus on the fact that a function is calculating the square root of a number (the *what*), instead of the fact that it is calling `math.sqrt()` to do it (the *how*). Unless we are writing performance tests or we have a particular need to verify how a certain action is performed, we ought to try to avoid this type of testing and focus on the *what*. Testing the *how* leads to restrictive tests and makes refactoring hard. Moreover, the type of test we have to write when we concentrate on the *how* is more likely to degrade the quality of our testing codebase when we amend the software frequently.
- **Tests should use the minimal set of fixtures needed to do the job**: This is another crucial point. Fixtures tend to grow over time. They also tend to change every now and then. If we use many fixtures and ignore redundancies in the tests, refactoring will take longer. Spotting bugs will be harder. We ought to try to use a set of fixtures that is big enough for the test to perform correctly, but not any bigger.
- **Tests should use as few resources as possible**: The reason for this is that every developer who checks out our code should be able to run the tests, no matter how powerful their machine is. It could be a skinny virtual machine or a CircleCI setup; tests should run without chewing up too many resources.
- **Tests should run as fast as possible**: A good test codebase could end up being much longer than the code being tested itself. It varies according to the situation and the developer, but, whatever the length, we will end up having hundreds, if not thousands, of tests to run, which means the faster they run, the faster we can get back to writing code. When using **TDD**, for example, we run tests very often, so speed is essential.

CircleCI is one of the largest **continuous integration/continuous delivery (CI/CD)** platforms available today. It is easy to integrate with services like GitHub, for example. You just need to add some configuration (typically in the form of a file) in the source code, and CircleCI will run tests when the new code is prepared to be merged into the current codebase.

Unit testing

Now that we have an idea about what testing is and why we need it, let us introduce the developer's best friend: the **unit test**.

Before we proceed with the examples, allow us to share some words of caution: we will try to give you the fundamentals about unit testing, but we do not follow any particular school of thought or methodology to the letter. Over the years, we have tried many different testing approaches, eventually coming up with our own way of doing things, which is constantly evolving. To put it as Bruce Lee would have:

> *Absorb what is useful, discard what is useless, and add what is specifically your own.*

Writing a unit test

Unit tests take their name from the fact that they are used to test small units of code. To explain how to write a unit test, let us look at a simple snippet:

```
# data.py
def get_clean_data(source):

    data = load_data(source)
    cleaned_data = clean_data(data)

    return cleaned_data
```

The `get_clean_data()` function is responsible for getting data from `source`, cleaning it, and returning it to the caller. How do we test this function?

One way of doing this is to call it and then make sure that `load_data()` was called once with `source` as its only argument. Then, we need to verify that `clean_data()` was called once, with the return value of `load_data()`. Finally, we would need to make sure that the return value of `clean_data()` is what is returned by the `get_clean_data()` function as well.

To do this, we need to set up the source and run this code, and this may be a problem. One of the golden rules of unit testing is that *anything that crosses the boundaries of your application needs to be simulated*. We do not want to talk to a real data source, and we do not want to actually run real functions if they are communicating with anything that is not contained in our application. A few examples would be a database, a search service, an external API, or the filesystem.

We need these restrictions to act as a shield so that we can always run our tests safely without the fear of destroying something in a real data source.

Another reason is that it may be quite difficult for a developer to reproduce the whole architecture on their machine. It may require the setting up of databases, APIs, services, files and folders, and so on, and this can be difficult, time-consuming, or sometimes not even possible.

Very simply put, an **API** is a set of tools for building software applications. An API expresses a software component in terms of its operations, input and output, and underlying types. For example, if you create software that needs to interface with a data provider service, it is likely that you will have to go through their API in order to gain access to the data.

Therefore, in our unit tests, we need to simulate all those things in some way. Unit tests need to be run by any developer without the need for the entire system to be set up on their machine.

A different approach, which we favor when it is possible to do so, is to simulate entities not by using fake objects but by using special-purpose test objects instead. For example, if our code talks to a database, instead of faking all the functions and methods that talk to the database and programming the fake objects so that they return what the real ones would, we would rather spawn a test database, set up the tables and data we need, and then patch the connection settings so that our tests are running real code against the test database. This is advantageous because if the underlying libraries change in a way that introduces an issue in our code, this setup will catch this issue. A test will break. A test with mocks, on the other hand, will blissfully continue to run successfully, because the mocked interface would have no idea about the change in the underlying library. In-memory databases are excellent options for these cases.

One of the applications that allows you to spawn a database for testing is Django. Within the `django.test` package, you can find several tools that help you write tests so that you won't have to simulate the dialog with a database. By writing tests this way, you will also be able to check on transactions, encodings, and all other database-related aspects of programming. Another advantage of this approach consists of the ability to check against details that can change from one database to another.

Sometimes, though, it is still not possible. For example, when the software interfaces with an API, and there is no test version of that API, we would need to simulate that API using fakes. In reality, most of the time we end up having to use a hybrid approach, where we use a test version of those technologies that allow this approach, and we use fakes for everything else. Let us now talk about fakes.

Mock objects and patching

First of all, in Python, these fake objects are called **mocks**. Up to version 3.3, the `mock` library was a third-party library that basically every project would install via pip but, from version 3.3, it has been included in the standard library under the `unittest` module, and rightfully so, given its importance and how widespread it is.

The act of replacing a real object or function (or in general, any piece of data structure) with a `mock` is called **patching**. The `mock` library provides the `patch` tool, which can act as a function or class decorator, and even as a context manager that you can use to `mock` things out.

Assertions

The verification phase is done through the use of assertions. In most cases, an **assertion** is a function or method that you can use to verify equality between objects, as well as other conditions. When a condition is not met, the assertion will raise an exception that will cause the test to fail. You can find a list of assertions in the `unittest` module documentation; however, when using `pytest`, you will typically use the generic `assert` statement, which makes things even simpler.

Testing a CSV generator

Let us now adopt a practical approach. We will show you how to test a small piece of code, and we will touch on the rest of the important concepts around unit testing within the context of this example.

We want to write an `export()` function that does the following: it takes a list of dictionaries, each of which represents a user. It creates a **comma-separated values** (**CSV**) file, puts a header in it, and then proceeds to add all the users who are deemed valid according to some rules. The function will take three parameters: the list of user dictionaries, the name of the CSV file to create, and an indication of whether an existing file with the same name should be overwritten.

To be considered valid, and added to the output file, a user dictionary must satisfy the following requirements: each user must have at least an email, a name, and an age. There can also be a fourth field representing the role, but it is optional. The user's email address needs to be valid, the name needs to be non-empty, and the age must be an integer between 18 and 65.

This is our task; so, now we are going to show you the code, and then we are going to analyze the tests we wrote for it. But, first things first, in the following code snippets, we will be using two third-party libraries: `marshmallow` and `pytest`. They are both in the requirements of the chapter's source code, so please make sure you have installed them with pip.

`marshmallow` (`https://marshmallow.readthedocs.io/`) is a library that provides us with the ability to serialize (or *dump*, in `marshmallow` terminology) and deserialize (or *load*, in `marshmallow` terminology) objects and, most importantly, gives us the ability to define a schema that we can use to validate a user dictionary. We will see another library that is used to create schemas, `pydantic`, in *Chapter 14*, *Introduction to API Development*.

`pytest` (`https://docs.pytest.org/`) is one of the best pieces of software we have ever seen. It is used almost everywhere and has replaced other libraries, such as *nose*. It provides us with useful tools to write tests quite efficiently.

Let us get to the code. We called it `api.py` just because it exposes a function that we can use to export the CSV. We will show it to you in chunks:

```
# api.py
from pathlib import Path
import csv
from copy import deepcopy

from marshmallow import Schema, fields, pre_load
from marshmallow.validate import Length, Range

class UserSchema(Schema):
    """Represent a *valid* user."""

    email = fields.Email(required=True)
    name = fields.Str(required=True, validate=Length(min=1))
    age = fields.Int(
        required=True, validate=Range(min=18, max=65)
    )
    role = fields.Str()

    @pre_load()
    def strip_name(self, data, **kwargs):
        data_copy = deepcopy(data)
        try:
            data_copy["name"] = data_copy["name"].strip()
        except (AttributeError, KeyError, TypeError):
            pass
        return data_copy
```

```
schema = UserSchema()
```

This first part is where we import all that we need (`Path`, `csv`, `deepcopy`, and some tools from `marshmallow`), and then we define the schema for the users. As you can see, we inherit from `marshmallow.Schema`, and then we set four fields. Notice we are using two string fields (`Str`), an `Email`, and an integer (`Int`). These will already provide us with some validation from `marshmallow`. Notice there is no `required=True` in the `role` field.

We need to add a couple of custom bits of code, though. We need to add validation on `age` to make sure the value is within the range we want. `marshmallow` will raise `ValidationError` if it is not. It will also take care of raising an error should we pass anything but an integer.

We also add validation on `name`, because the fact that there is a `name` key in a dictionary does not guarantee that the value of that name is non-empty. We validate that the length of the field's value is at least one. Notice we do not need to add anything for the `email` field. This is because `marshmallow` will validate it for us.

After the field declarations, we write another method, `strip_name()`, which is decorated with the `pre_load()` `marshmallow` helper. This method will run before `marshmallow` deserializes (loads) the data. As you can see, we make a copy of `data` first, as in this context it is not a good idea to work directly on a mutable object, and then make sure we strip leading and trailing spaces away from `data['name']`. That key represents the name field we just declared above. We make sure we do this within a `try/except` block, so deserialization can run smoothly even in case of errors. The method returns the modified copy of `data`, and `marshmallow` does the rest.

We then instantiate `schema`, so that we can use it to validate data. So, let us write the `export` function:

```
# api.py
def export(filename, users, overwrite=True):
    """Export a CSV file.

    Create a CSV file and fill with valid users.  If `overwrite`
    is False and file already exists, raise IOError.
    """
    if not overwrite and Path(filename).is_file():
        raise IOError(f"'{filename}' already exists.")

    valid_users = get_valid_users(users)
    write_csv(filename, valid_users)
```

As you see, its logic is straightforward. If `overwrite` is `False` and the file already exists, we raise `IOError` with a message saying the file already exists. Otherwise, if we can proceed, we simply get the list of valid users and feed it to `write_csv()`, which is responsible for actually doing the job. Let us see how all these functions are defined:

```
# api.py
def get_valid_users(users):
    """Yield one valid user at a time from users."""
    yield from filter(is_valid, users)

def is_valid(user):
    """Tell if the user is valid."""
    return not schema.validate(user)
```

We coded `get_valid_users()` as a generator, as there is no need to make a potentially big list before writing to a file. We can validate and save them one by one. The `is_valid()` function simply delegates to `marshmallow`'s `schema.validate()` to validate the user. This method returns a dictionary, which is empty if the data is valid according to the schema or else it will contain error information. We do not need to collect the error information for this task, so we simply ignore it, and the `is_valid()` function simply returns `True` if the return value from `schema.validate()` is empty, or `False` otherwise.

The final piece of code in this module is:

```
# api.py
def write_csv(filename, users):
    """Write a CSV given a filename and a list of users.

    The users are assumed to be valid for the given CSV structure.
    """
    fieldnames = ["email", "name", "age", "role"]

    with open(filename, "w", newline="") as csvfile:
        writer = csv.DictWriter(csvfile, fieldnames=fieldnames)
        writer.writeheader()
        writer.writerows(users)
```

Again, the logic is straightforward. We define the header in `fieldnames`, then we open `filename` for writing, and we specify `newline=""`, which is recommended in the documentation for CSV files.

When the file has been created, we get a `writer` object by using the `csv.DictWriter` class. This tool maps the user dictionaries to the field names, so we do not need to take care of the ordering.

We write the header first, and then we loop over the users and add them one by one. Notice that this function assumes it is fed a list of valid users, and it may break if that assumption is false (with the default values, it would break if any user dictionary had extra fields).

That's the code you should try and keep in mind. We suggest you spend a moment going through it again. There is no need to memorize it, and the fact that we have used small helper functions with meaningful names will enable you to follow the testing more easily.

Let us now get to the interesting part: testing the `export()` function. Once again, we will show you the code in chunks:

```
# tests/test_api.py
import re
from unittest.mock import patch, mock_open, call
import pytest
from api import is_valid, export, write_csv
```

Let us start with the imports: first, we import the `re` module from the standard library, as it's needed in one of the tests. Then, we bring in some tools from `unittest.mock`, then `pytest`, and, finally, we fetch the three functions that we want to actually test: `is_valid()`, `export()`, and `write_csv()`.

Before we can write tests, though, we need to make a few fixtures. As you will see, a **fixture** in `pytest` is a function decorated with the `pytest.fixture` decorator. Fixtures are run before each test to which they are applied. In most cases, we expect a fixture to return something so that we can use it in a test. We have some requirements for a user dictionary, so let us write a couple of users: one with minimal requirements, and one with full requirements. Both need to be valid. Here is the code:

```
# tests/test_api.py
@pytest.fixture
def min_user():
    """Represent a valid user with minimal data."""
    return {
        "email": "minimal@example.com",
        "name": "Primus Minimus",
        "age": 18,
```

```
    }

@pytest.fixture
def full_user():
    """Represent valid user with full data."""
    return {
        "email": "full@example.com",
        "name": "Maximus Plenus",
        "age": 65,
        "role": "emperor",
    }
```

In this example, the only difference between the users is the presence of the `role` key, but it should be enough to show you the point.

Notice that instead of simply declaring dictionaries at a module level, we have actually written two functions that return a dictionary, and we have decorated them with the `@pytest.fixture` decorator. This is because when you declare a dictionary that is supposed to be used in your tests at the module level, you need to make sure you copy it at the beginning of every test. If you do not, and any of the tests (or the code being tested) modify it, all the following tests might be compromised, as the dictionary would not be in its original form. By using these fixtures, `pytest` will give us a new dictionary for every test, so we do not need to go through that copy procedure. This helps to respect the principle of independence, which says that each test should be self-contained and independent.

Fixtures are also *composable*, which means they can be used in one another, which is a useful feature of `pytest`. To show you this, let us write a fixture for a list of users, in which we put the two we already have, plus one that would fail validation because it has no age. Let us take a look at the following code:

```
# tests/test_api.py
@pytest.fixture
def users(min_user, full_user):
    """List of users, two valid and one invalid."""
    bad_user = {
        "email": "invalid@example.com",
        "name": "Horribilis",
    }
    return [min_user, bad_user, full_user]
```

We now have two users that we can use individually, and we also have a list of three users.

The first few tests will test how we validate a user. We will group all the tests for this task within a class. This helps to give related tests a namespace, a place to be. As we will see later, it also allows us to declare class-level fixtures, which are defined just for the tests belonging to the class. One of the benefits of declaring a fixture at a class level is that you can easily override one with the same name that lives outside the scope of the class.

Although, in this case, we found it convenient to organize our tests in classes, you can also just have tests defined at the module level. `pytest` allows for great flexibility in the way tests are structured.

Moreover, you will notice, as we walk you through the examples, that the name of each test function starts with `test_` and that of each test class starts with `Test`. This is to allow `pytest` to discover these functions and classes and consider them as tests. Please refer to the pytest documentation to learn the full specifications.

Let us come back to our code now. Take a look at the following:

```
# tests/test_api.py
class TestIsValid:
    """Test how code verifies whether a user is valid or not."""

    def test_minimal(self, min_user):
        assert is_valid(min_user)

    def test_full(self, full_user):
        assert is_valid(full_user)
```

We start very simply by making sure our fixtures actually pass validation. This helps ensure that our code will correctly validate users that we know to be valid, with minimal as well as full data. Notice that we gave each test function a parameter matching the name of a fixture. This has the effect of activating the fixture for that test. When `pytest` runs the tests, it will inspect the parameters of each test and pass the return values of the corresponding fixture functions as arguments to the test.

Before we proceed, it would be good to run these two tests, just to make sure everything is wired up correctly. To run the tests, we invoke the `pytest` command in the shell, from the `ch10` folder:

```
$ pytest tests -vv
==================== test session starts ====================
platform darwin -- Python 3.12.2, pytest-8.1.1, pluggy-1.4.0 --
```

```
  /Users/fab/.virtualenvs/lpp4ed-ch10/bin/python
cachedir: .pytest_cache
rootdir: /Users/fab/code/lpp4ed
configfile: pyproject.toml
collected 2 items

tests/test_api.py::TestIsValid::test_minimal PASSED      [ 50%]
tests/test_api.py::TestIsValid::test_full PASSED         [100%]
====================== 2 passed in 0.03s ======================
```

We have instructed the command to search for tests in the `tests` folder. Moreover, to show you the full details, we have invoked it with the verbose flag (`-vv`).

After a bit of boilerplate, we find two lines that we highlighted. They represent the full path to each of the tests that ran. First, the name of the module where the tests live, then in this case, the name of the class in which they are defined, and finally their names.

On the right, you can see the progression, indicated as a percentage. In this case, we only have two tests for now, so after running the first one, we have completed 50% of the test suite, and 100% after the second one. They both passed.

Should any of the tests fail, `pytest` would print an error and some debug information, so we can inspect what is wrong and fix it. Let us simulate a failure by removing the `name` key from the `min_user` fixture and running the tests again:

```
$ pytest tests -vv
===================== test session starts =====================
platform darwin -- Python 3.12.2, pytest-8.1.1, pluggy-1.4.0 --
/Users/fab/.virtualenvs/lpp4ed-ch10/bin/python
cachedir: .pytest_cache
rootdir: /Users/fab/code/lpp4ed
configfile: pyproject.toml
collected 2 items

tests/test_api.py::TestIsValid::test_minimal FAILED     [ 50%]
tests/test_api.py::TestIsValid::test_full PASSED        [100%]
========================== FAILURES ===========================
_____________________ TestIsValid.test_minimal ______________________
```

```
self = <ch10.tests.test_api.TestIsValid object at 0x103603920>,
       min_user = {'age': 18, 'email': 'minimal@example.com'}

    def test_minimal(self, min_user):
>       assert is_valid(min_user)
E       AssertionError: assert False
E        +  where False = is_valid(
               {'age': 18, 'email': 'minimal@example.com'}
           )

tests/test_api.py:45: AssertionError
================== short test summary info ==================
FAILED tests/test_api.py::TestIsValid::test_minimal
       - AssertionError: assert False
================ 1 failed, 1 passed in 0.04s ================
```

As you can see in the highlighted sections, `pytest` reports which tests failed, and a snippet of the code where the failure happened, so we can inspect it and discover what the problem is. On the left-hand side of the snippet, there is a > sign, which indicates the line that threw the error, and underneath, two lines representing the error itself, which in this case is that `{'age': 18, 'email': 'minimal@example.com'}` is not a valid user.

Now that we know how to run tests, please feel free to run them any time you want. A good practice when we run tests is to make sure that they would fail if something was wrong, so feel free to play around with the fixtures and the assertions.

Let us go back to the test suite now. The next task is to test the age. To do that, we are going to use parametrization.

Parametrization is a technique that enables us to run the same test multiple times but feed different data to it. It is quite useful as it allows us to write the test only once with no repetition, and the result will be intelligently handled by `pytest`, which will run all those tests as if they were actually separate, thus providing us with clear error messages when they fail. Another solution would be to write one test with a `for` loop inside that runs through all the pieces of data we want to test against. The latter solution is of much lower quality though, as the framework won't be able to give you specific information as if you were running separate tests. Moreover, should any of the `for` loop iterations fail, there would be no information about what would have happened after that, as subsequent iterations will not happen. Finally, the body of the test would get more difficult to understand, due to the `for` loop extra logic. Therefore, parametrization is a far superior choice for this use case.

It also spares us from having to write a bunch of almost identical tests to exhaust all possible scenarios. Let us see how we test the age (we are repeating the class signature for you, but omitting the tests that have already been presented):

```
# tests/test_api.py
class TestIsValid:
    …
    @pytest.mark.parametrize("age", range(18))
    def test_invalid_age_too_young(self, age, min_user):
        min_user["age"] = age
        assert not is_valid(min_user)
```

We start by writing a test to check that validation fails when the user is too young. According to our rule, a user is too young when they are younger than 18. We check for every age between 0 and 17 by using `range()`.

If you look at how the parametrization works, you see that we declare the name of an object and age and then we specify which values this object will take. The test will be run once for each of the specified values. In the case of this first test, the values are all those returned by `range(18)`, which means all integer numbers from 0 to 17 are included. Note that we also add an age parameter to the test. The values specified in the parameterization will be passed as arguments to the test through this parameter.

We also use the `min_user()` fixture in this test. In this case, we change the age within the `min_user()` dictionary, and then we verify that the result of `is_valid(min_user)` is `False`. We do this by asserting the fact that `not False` is `True`. In `pytest`, this is how you check for something. You simply assert that something is truthy. If that is the case, the test has succeeded. Should it instead be the opposite, the test will fail.

Note that `pytest` will re-evaluate the fixture function for each test run that uses it, so we are free to modify the fixture data within the test without affecting any other tests.

Let us proceed and add all the tests needed to make validation fail on the age:

```
# tests/test_api.py
class TestIsValid:
    ...
    @pytest.mark.parametrize("age", range(66, 100))
```

```
    def test_invalid_age_too_old(self, age, min_user):
        min_user["age"] = age
        assert not is_valid(min_user)

    @pytest.mark.parametrize("age", ["NaN", 3.1415, None])
    def test_invalid_age_wrong_type(self, age, min_user):
        min_user["age"] = age
        assert not is_valid(min_user)
```

Another two tests. One takes care of the other end of the spectrum, from 66 years of age to 99. The second one instead makes sure that age is invalid when it is not an integer number, so we pass some values, such as a string, a float, and `None`, just to make sure. Notice how the structure of these tests is all the same, but, thanks to the parametrization, we feed different input arguments to it.

Now that we have the age-failing logic sorted out, let us add a test that checks when age is within the valid range:

```
# tests/test_api.py
class TestIsValid:
    ...
    @pytest.mark.parametrize("age", range(18, 66))
    def test_valid_age(self, age, min_user):
        min_user["age"] = age
        assert is_valid(min_user)
```

It is as easy as that. We pass the correct range, from 18 to 65, and remove the `not` in the assertion.

We can consider the age as being taken care of. Let us move on to write tests on mandatory fields:

```
# tests/test_api.py
class TestIsValid:
    ...
    @pytest.mark.parametrize("field", ["email", "name", "age"])
    def test_mandatory_fields(self, field, min_user):
        del min_user[field]
        assert not is_valid(min_user)

    @pytest.mark.parametrize("field", ["email", "name", "age"])
    def test_mandatory_fields_empty(self, field, min_user):
        min_user[field] = ""
        assert not is_valid(min_user)
```

```
    def test_name_whitespace_only(self, min_user):
        min_user["name"] = " \n\t"
        assert not is_valid(min_user)
```

These three tests still belong to the same class. The first one tests whether a user is invalid when one of the mandatory fields is missing. Remember that at every test run, the `min_user` fixture is restored, so we only have one missing field per test run, which is the appropriate way to check for mandatory fields. We simply remove that one key from the dictionary. This time, the parametrization object takes the name `field`, and, by looking at the first test, you see all the mandatory fields in the parametrization decorator: `email`, `name`, and `age`.

In the second one, things are a little different. Instead of removing keys, we simply set them (one at a time) to the empty string. Finally, in the third one, we check for the name to be made of whitespace only.

The previous tests take care of mandatory fields being there and being non-empty, and of the formatting around the `name` key of a user. Let us now write the last two tests for this class. We want to check that email is valid, and in the second one, the type for email, name, and role:

```
# tests/test_api.py
class TestIsValid:
    ...
    @pytest.mark.parametrize(
        ("email", "outcome"),
        [
            ("missing_at.com", False),
            ("@missing_start.com", False),
            ("missing_end@", False),
            ("missing_dot@example", False),
            ("good.one@example.com", True),
            ("δοκιμή@παράδειγμα.δοκιμή", True),
            ("аджай@экзампл.рус", True),
        ],
    )
    def test_email(self, email, outcome, min_user):
        min_user["email"] = email
        assert is_valid(min_user) == outcome
```

This time, the parametrization is slightly more complex. We define two objects (`email` and `outcome`) and then we pass a list of tuples, instead of a simple list, to the decorator. Each time the test is run, one of those tuples will be unpacked to fill the values of `email` and `outcome`, respectively. This allows us to write one test for both valid and invalid email addresses, instead of two separate ones. We define an email address, and we specify the outcome we expect from validation. The first four are invalid email addresses, and the last three are valid. We have used a couple of examples with non-ASCII characters, just to make sure we are not forgetting to include our friends from all over the world in the validation.

Notice how the validation is done, asserting that the result of the call needs to match the outcome we have set.

Let us now write a simple test to make sure validation fails when we feed the wrong type to the fields (again, the age has been taken care of separately before):

```
# tests/test_api.py
class TestIsValid:
    ...
    @pytest.mark.parametrize(
        ("field", "value"),
        [
            ("email", None),
            ("email", 3.1415),
            ("email", {}),
            ("name", None),
            ("name", 3.1415),
            ("name", {}),
            ("role", None),
            ("role", 3.1415),
            ("role", {}),
        ],
    )
    def test_invalid_types(self, field, value, min_user):
        min_user[field] = value
        assert not is_valid(min_user)
```

As we did before, we pass three different values, none of which is actually a string. This test could be expanded to include more values, but, honestly, we shouldn't need to write tests such as this one. We have included it here just to show you what's possible, but normally you would focus on making sure the code considers valid types, those that have to be considered valid, and that should be enough.

Before we move to the next test class, let us take a moment to talk a bit more about something we briefly touched on when testing the age.

Boundaries and granularity

While checking for the age, we wrote three tests to cover the three ranges: 0-17 (fail), 18-65 (success), and 66-99 (fail). Why did we do this? The answer lies in the fact that we are dealing with two boundaries: 18 and 65. So, our testing needs to focus on the three regions those two boundaries define: before 18, within 18 and 65, and after 65. How you do it is not important, as long as you make sure you test the boundaries correctly. This means if someone changes the validation in the schema from `18 <= value <= 65` to `18 <= value < 65` (notice the second `<=` is now `<`), there must be a test that fails on 65.

This concept is known as a **boundary**, and it is crucial that you recognize them in your code so that you can test against them.

Another important thing is to understand how close to the boundaries to get. In other words, which unit should I use to approach them?

In the case of age, we are dealing with integers, so a unit of 1 will be the perfect choice (which is why we used 16, 17, 18, 19, 20, ...). But what if you were testing for a timestamp? Well, in that case, the correct granularity will likely be different. If the code has to act differently according to your timestamp and that timestamp represents seconds, then the granularity of your tests should zoom down to seconds. If the timestamp represents years, then years should be the unit you use. We hope you get the picture. This concept is known as **granularity** and needs to be combined with that of boundaries so that by going around the boundaries with the correct granularity, you can make sure your tests are not leaving anything to chance.

Let us now continue with our example and test the `export` function.

Testing the export function

In the same test module, we defined another class that represents a test suite for the `export()` function. Here it is:

```
# tests/test_api.py
class TestExport:
    """Test behavior of `export` function."""

    @pytest.fixture
    def csv_file(self, tmp_path):
        """Yield a filename in a temporary folder.

        Due to how pytest `tmp_path` fixture works, the file does
        not exist yet.
        """
        csv_path = tmp_path / "out.csv"
        yield csv_path
        csv_path.unlink(missing_ok=True)

    @pytest.fixture
    def existing_file(self, tmp_path):
        """Create a temporary file and put some content in it."""
        existing = tmp_path / "existing.csv"
        existing.write_text("Please leave me alone...")
        return existing
```

Let us start by analyzing the fixtures. We have defined them at the class level this time, which means they will be available for the tests in the same class. We do not need these fixtures outside of this class, so it does not make sense to declare them at a module level as we did with the user ones.

We need two files. If you recall what we wrote at the beginning of this chapter, when it comes to interaction with databases, disks, networks, and so on, we should `mock` everything out. However, when possible, we prefer to use a different technique. In this case, we will employ temporary folders, which will be created and deleted within the fixture. We are much happier if we can avoid mocking. To create temporary folders, we employ the `tmp_path` fixture, from `pytest`, which is a `pathlib.Path` object.

The first fixture, `csv_file()`, provides a reference to a temporary folder. We can consider the logic up to and including the `yield` as the setup phase. The fixture itself, in terms of data, is represented by the temporary filename. The file itself does not exist yet. When a test runs, the fixture is created, and at the end of the test, the rest of the fixture code (the part after `yield`, if any) is executed.

That part can be considered the teardown phase. In the case of the `csv_file()` fixture, it consists of calling `csv_path.unlink()` to delete the `.csv` file (if it exists). You can put much more in each phase of any fixture, and with experience, you will master the art of doing setup and teardown this way. It comes naturally quite quickly.

It is not strictly necessary to delete the `.csv` file after each test. The `tmp_path` fixture will create a new temporary directory for each test, so there is no risk of files created within this directory interfering with other tests. We chose to delete the file in this fixture only to demonstrate the use of `yield` in fixtures.

The second fixture, `existing_file()`, is quite similar to the first one, but we will use it to test that we can prevent overwriting when we call `export()` with `overwrite=False`. So, we create a file in the temporary folder, and we put some content into it, just to have the means to verify it hasn't been touched.

Let us now see the tests (as we did before, we include the class declaration but omit tests which we already presented):

```
# tests/test_api.py
class TestExport:
    ...
    def test_export(self, users, csv_file):
        export(csv_file, users)
        text = csv_file.read_text()

        assert (
            "email,name,age,role\n"
            "minimal@example.com,Primus Minimus,18,\n"
            "full@example.com,Maximus Plenus,65,emperor\n"
        ) == text
```

This test employs the `users()` and `csv_file()` fixtures, and immediately calls `export()` with them. We expect that a file has been created, and populated with the two valid users we have (remember the list contains three users, but one is invalid).

To verify that, we open the temporary file and collect all its text into a string. We then compare the content of the file with what we expect to be in it. Notice we only put the header, and the two valid users, in the correct order.

Now we need another test to make sure that if there is a comma in one of the values, our CSV is still generated correctly. Being a **CSV** file, we need to make sure that a comma in the data does not break things up:

```
# tests/test_api.py
class TestExport:
    ...
    def test_export_quoting(self, min_user, csv_file):
        min_user["name"] = "A name, with a comma"
        export(csv_file, [min_user])
        text = csv_file.read_text()

        assert (
            "email,name,age,role\n"
            'minimal@example.com,"A name, with a comma",18,\n'
        ) == text
```

This time, we do not need the whole users list; we just need one, as we are testing a specific thing and we have the previous test to make sure we are generating the file correctly with all the users. Remember, always try to minimize the work you do within a test.

So, we use `min_user()` and put a comma in its name. We then repeat the procedure, which is similar to that of the previous test, and finally, we make sure that the name is put in the CSV file surrounded by double quotes. This is enough for any good CSV parser to understand that they should not break the comma inside the double quotes.

Now, we want one more test, to check that when the file already exists and we do not want to override it, our code won't do that:

```
# tests/test_api.py
class TestExport:
    ...
    def test_does_not_overwrite(self, users, existing_file):
        with pytest.raises(IOError) as err:
            export(existing_file, users, overwrite=False)

        err.match(
            r"'{}' already exists\.".format(
                re.escape(str(existing_file))
            )
```

```
        )

        # let us also verify the file is still intact
        assert existing_file.read_text() == (
            "Please leave me alone..."
        )
```

This is an interesting test because it allows us to show you how you can tell `pytest` that you expect a function call to raise an exception. We do it in the context manager given to us by `pytest.raises()`, to which we feed the exception we expect from the call we make inside the body of that context manager. If the exception is not raised, the test will fail.

We like to be thorough in our tests, so we do not want to stop there. We also assert on the message, by using the convenient `err.match()` helper. Notice that we do not need to use an `assert` statement when calling `err.match()`. If the argument does not match, the call will raise an `AssertionError`, causing the test to fail. We also need to escape the string version of `existing_file` because on Windows, paths have backslashes, which would confuse the regular expression we feed to `err.match()`.

Finally, we make sure that the file still contains its original content (which is why we created the `existing_file()` fixture) by reading it and comparing its content to the string we originally wrote to the file.

Final considerations

Before we move on to the next topic, let us wrap up with some considerations.

First, we hope you have noticed that we haven't tested all the functions we wrote. Specifically, we didn't test `get_valid_users()`, `validate()`, and `write_csv()`. The reason is that these functions are already implicitly tested by our test suite. We have tested `is_valid()` and `export()`, which is more than enough to make sure the schema is validating users correctly, and that the `export()` function is filtering out invalid users, respecting existing files when needed, and writing a proper CSV. The functions we haven't tested are the internals; they provide logic that participates in doing something that we have thoroughly tested anyway.

Would adding extra tests for those functions be good or bad? The answer is actually difficult.

The more we test, the less easily we can refactor that code. As it is now, we could easily decide to rename `validate()`, and we wouldn't have to change any of the tests we wrote. If you think about it, it makes sense, because as long as `validate()` provides correct validation to the `get_valid_users()` function, we do not really need to know about it.

If, instead, we had written tests for the `validate()` function, then we would have to change them, had we decided to rename it (or to change its signature, for example).

So, what is the right thing to do? Tests or no tests? It will be up to you. You have to find the right balance. Our personal take on this matter is that everything needs to be thoroughly tested, either directly or indirectly. We try to write the smallest possible test suite that guarantees that. This way, we will have a complete test suite in terms of coverage, but not any bigger than necessary. We need to maintain those tests.

We hope this example made sense to you; we think it has allowed us to touch on the important topics.

If you check out the source code for the book, in the `test_api.py` module, you will find a couple of extra test classes that will show you how different testing would have been had we decided to go all the way with the mocks. Make sure you read that code and understand it well. It is quite straightforward and will offer you a good comparison with the approach we have shown you here.

Let us now run the full test suite:

```
$ pytest tests
====================== test session starts ======================
platform darwin -- Python 3.12.2, pytest-8.1.1, pluggy-1.4.0
rootdir: /Users/fab/code/lpp4ed
configfile: pyproject.toml
collected 132 items

tests/test_api.py ..........................................
............................................................
.....................                                  [100%]

====================== 132 passed in 0.14s ======================
```

As mentioned before, make sure you run `$ pytest test` from within the `ch10` folder (add the `-vv` flag for a verbose output that will show you how parametrization modifies the names of your tests). `pytest` scans your files and folders, searching for modules that start or end with `test_`, like `test_*.py` or `*_test.py`. Within those modules, it grabs `test`-prefixed functions or `test`-prefixed methods inside `Test`-prefixed classes (you can read the full specification in the `pytest` documentation). As you can see, 132 tests were run in 140 milliseconds, and they all succeeded. We strongly suggest you check out this code and experiment with it. Change something in the code and see whether any test fails. Understand why it fails (or does not).

Did the tests pass even though the code is no longer correct? Are the tests too rigid and failing even when you make a change that does not affect the correctness of the output? Thinking about these questions will help you gain a deeper insight into the art of testing.

We also suggest you study the `unittest` module, and the `pytest` library too. These are tools you will use all the time, so you need to be familiar with them.

Let us now discuss TDD.

Test-driven development

Let us talk briefly about **TDD**. It is a methodology that was rediscovered by Kent Beck, who wrote *Test-Driven Development by Example, Addison Wesley, 2002*, which we encourage you to read if you want to learn about the fundamentals of this subject.

TDD is a software development methodology that is based on the continuous repetition of a very short development cycle.

First, the developer writes a test and makes it run. The test is supposed to check a feature that is not yet part of the code. Maybe it is a new feature to be added or something to be removed or amended. Running the test will make it fail and, because of this, this phase is called **Red**.

The developer then writes the minimal amount of code to make the test pass. When the test run succeeds, we have the so-called **Green** phase. In this phase, it is okay to write code that cheats, just to make the test pass. This technique is called *fake it 'til you make it*. In a second iteration of the TDD cycle, tests are enriched with different edge cases, and if there is any cheating code, it will not be able to satisfy all the tests simultaneously, therefore the developer will have to write the actual logic that satisfies the tests. Adding other test cases is sometimes called **triangulation**.

The last piece of the cycle is where the developer takes care of refactoring code and tests until they are in the desired state. This last phase is called **Refactor**.

The TDD mantra therefore is **Red-Green-Refactor**.

At first, it might feel weird to write tests before the code, and we must confess it took us a while to get used to it. If you stick to it, though, and force yourself to learn this slightly counterintuitive method, at some point, something almost magical happens, and you will see the quality of your code increase in a way that would not have been possible otherwise.

When we write our code before the tests, we must take care of *what* the code has to do and *how* it has to do it, both at the same time. On the other hand, when we write tests before the code, we can concentrate on the *what* part almost exclusively.

Afterward, when we write the code, we will mostly have to take care of *how* the code has to implement *what* is required by the tests. This shift in focus allows our minds to concentrate on the *what* and *how* parts separately, yielding a brainpower boost that can feel quite surprising.

There are several other benefits that come from the adoption of this technique:

- **Improved code quality**: Writing tests first ensures that the codebase is thoroughly tested and can lead to fewer bugs and errors in the production code. It encourages developers to write only the code necessary to pass tests, which can result in cleaner, simpler code.
- **Better design decisions**: TDD encourages developers to think about the design and structure of the code from the beginning. This early consideration can lead to better software design and architecture.
- **Facilitates refactoring**: With a comprehensive suite of tests in place, developers can confidently refactor and improve the code, knowing that the tests will catch any regressions or issues introduced by changes.
- **Documentation**: The tests themselves serve as documentation for the codebase. They describe what the code is supposed to do, which can be helpful for new team members or when revisiting old code.
- **Reduces time spent on debugging**: By catching errors early in the development process, TDD can reduce the amount of time developers spend debugging code.
- **Better understanding of business requirements**: Having a suite of tests that pass gives developers confidence that their code meets the required specifications and behaves as expected.

On the other hand, there are some shortcomings of this technique:

- **Initial slowdown**: Writing tests before writing functional code can slow down the initial development process. This can be particularly challenging in fast-paced development environments or for tight deadlines.
- **Learning curve**: TDD requires a different mindset and approach to coding than what many developers are accustomed to. There can be a significant learning curve, and developers may initially find it difficult to write effective tests.
- **Overhead for simple changes**: For very simple changes or fixes, the overhead of writing a test first can seem unnecessary and time-consuming.
- **Difficulty with complex UI or external systems**: Testing can become challenging when dealing with complex UIs or interactions with external systems, databases, or APIs. Mocking and stubbing can help, but they also add complexity and maintenance overhead.

We are quite passionate about TDD. However, through years of application, we have encountered scenarios where TDD proves to be less feasible. A prime example is when faced with test suites comprising hundreds or even thousands of tests. In such instances, predetermining the specific tests to alter for a desired change in the source code becomes an almost insurmountable task. It may, at times, be more pragmatic to directly modify the code and observe which tests fail as a result.

Nonetheless, we maintain a firm belief in the value of mastering TDD. While the most significant advantages of TDD may lie in its educational merits rather than its practical application, the knowledge and mindset it instills are invaluable. Mastering TDD to the extent that it can be applied efficiently leaves an indelible mark on our coding practices, influencing our approach even in projects where TDD is not utilized.

It is essential, therefore, to bear in mind the following principle: always rigorously test your code. This practice is fundamental to ensuring the reliability and integrity of software, regardless of the development methodology employed.

Summary

In this chapter, we explored the world of testing.

We tried to give you a fairly comprehensive overview of testing, especially unit testing, which is the most common type of testing a developer does. We hope we have succeeded in conveying the message that testing is not something that is perfectly defined and that you can learn from a book. You need to experiment with it for a significant amount of time before you get comfortable. Of all the efforts a coder must make in terms of study and experimentation, we would say testing is amongst the most important.

In the next chapter, we are going to explore debugging and profiling, which are techniques that go hand in hand with testing. You should make sure you learn them well.

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11

Debugging and Profiling

> *"If debugging is the process of removing software bugs, then programming must be the process of putting them in."*
>
> *– Edsger W. Dijkstra*

In the life of a professional coder, debugging and troubleshooting take up a significant amount of time. All but the most trivial software is guaranteed to have bugs. Humans are not perfect; we make mistakes. Therefore, the code we produce is also not perfect. As developers, we spend a large portion of our time reading code that was written by other people. In our opinion, a good software developer is someone who keeps an eye out for potential bugs, even when they are reading code that is not reported to be wrong or buggy.

Being able to debug code efficiently and quickly is a skill that every coder needs to keep improving. Like testing, debugging is a skill that is best learned through experience. There are guidelines you can follow, but there is no book that will teach you everything you need to know to become good at this.

We feel that on this subject, we have learned the most from our colleagues. It amazes us to observe someone who is very skilled attacking a problem. We enjoy seeing the steps they take, the things they verify to exclude potential causes, and how they select the path that eventually leads them to a solution.

Every colleague we work with can teach us something or surprise us with a fantastic guess that turns out to be the right one. When that happens, do not just remain in wonderment (or worse, in envy), but seize the moment and ask them how they got to that guess and why. The answer will allow you to see whether there is something you can study in depth later so that, next time, you will be the one who finds the bug.

Some bugs are easy to spot. They come out of mistakes and, once you see the effects of those mistakes, it is easy to find a solution to the problem. But there are other bugs that are much more subtle and require true expertise and a great deal of creativity and out-of-the-box thinking to be dealt with. The worst bugs of all are the non-deterministic ones. These sometimes happen, and sometimes do not. Some happen only in a particular environment but not in another seemingly identical environment.

In a professional setting, we often need to debug our code in highly stressful situations. If a website is down, or customers are upset, the business is losing money. As a result, there is often a lot of pressure on developers to find and fix the problem immediately. In such situations, it is crucial to be able to keep calm. That's the most important skill to have if you want to be able to fight bugs effectively. Stress negatively impacts the creative thinking and problem-solving abilities that we need to find and fix bugs. So, take a deep breath, sit properly, and focus.

In this chapter, we will try to demonstrate some useful techniques that you can employ according to the severity of the bug, and a few suggestions that will hopefully boost your weapons against bugs and issues.

Specifically, we are going to look at the following:

- Debugging techniques
- Troubleshooting guidelines
- Profiling

Debugging techniques

In this part, we will introduce you to some of the techniques we use most often. This is not an exhaustive list, but it should give you some useful ideas for where to start when debugging your own Python code.

Debugging with print

The key to understanding any bug is to understand what your code is doing at the point where the bug occurs. For this reason, we will be looking at a few different techniques for inspecting the state of a program while it is running.

The easiest technique of all is to add `print()` calls at various points in your code. This allows you to easily see which parts of your code are executed, and what the values of key variables are at different points during execution. For example, if you are developing a Django website and what happens on a page is not what you would expect, you can fill the view with prints and keep an eye on the console while you reload the page.

There are several drawbacks and limitations to using `print()` for debugging. To use this technique, you need to be able to modify the source code and run it in a terminal where you can see the output of your `print()` function calls. This is not a problem in your development environment on your own machine, but it does limit the usefulness of this technique in other environments.

When you scatter calls to `print()` in your code, you can easily end up duplicating a lot of debugging code. For example, you may want to print timestamps (like we did when we were measuring how fast list comprehensions and generators were), or somehow build up a string with the information that you want to display. Another disadvantage of this technique is that it is easy to forget calls to `print()` in your code.

For these reasons, we sometimes prefer to use a custom debugging function rather than just bare calls to `print()`. Let us see how.

Debugging with a custom function

Having a custom debugging function saved in a file somewhere that you can quickly grab and paste into the code can be particularly useful. If you are fast, you can also code one on the fly. The important thing is to write it in such a way that it will not leave anything behind when you eventually remove the calls and their definitions. Therefore, *it is important to code it in a way that is completely self-contained*. Another good reason for this requirement is that it will avoid potential name clashes with the rest of the code.

Let us see an example of such a function:

```
# custom.py
def debug(*msg, print_separator=True):
    print(*msg)
    if print_separator:
        print("-" * 40)

debug("Data is ...")
debug("Different", "Strings", "Are not a problem")
debug("After while loop", print_separator=False)
```

In this case, we are using a keyword-only argument to be able to print a separator, which is a line of 40 dashes.

The function just passes whatever is in `msg` to a call to `print()` and, if `print_separator` is `True`, it prints a line separator. Running the code will show the following:

```
$ python custom.py
Data is ...
----------------------------------------
Different Strings Are not a problem
----------------------------------------
After while loop
```

As you can see, there is no separator after the last line.

This is just one easy way to augment a simple call to the `print()` function. Let us see how we can calculate a time difference between calls, using one of Python's tricky features to our advantage:

```
# custom_timestamp.py
from time import sleep
def debug(*msg, timestamp=[None]):
    from time import time  # local import
    print(*msg)
    if timestamp[0] is None:
        timestamp[0] = time()  # 1
    else:
        now = time()
        print(f" Time elapsed: {now - timestamp[0]:.3f}s")
        timestamp[0] = now  # 2

debug("Entering buggy piece of code...")
sleep(0.3)
debug("First step done.")
sleep(0.5)
debug("Second step done.")
```

This is a bit more complicated. First, notice that we used an `import` statement *inside* the `debug()` function to import the `time()` function from the `time` module. This allows us to avoid having to add that `import` outside the function and risk forgetting to remove it.

Look at how we defined `timestamp`. It is a function parameter with a list as its default value. In *Chapter 4*, *Functions, the Building Blocks of Code*, we warned against using mutable defaults for parameters because the default value is initialized when Python parses the function, and the same object persists across different calls to the function. Most of the time, this is not the behavior you want. In this case, however, we are taking advantage of this feature to store a timestamp from the previous call to the function, without having to use an external global variable. We borrowed this trick from our studies on **closures**, a technique that we encourage you to read about.

After printing the message, we inspect the content of the only item in `timestamp`. If it is `None`, we have no previous timestamp, so we set the value to the current time (`#1`). On the other hand, if we have a previous timestamp, we can calculate a difference (which we neatly format to three decimal digits), and finally, we put the current time in `timestamp` (`#2`).

Running this code outputs the following:

```
$ python custom_timestamp.py
Entering buggy piece of code...
First step done.
 Time elapsed: 0.300s
Second step done.
 Time elapsed: 0.500s
```

Using a custom debug function solves some of the problems associated with just using `print()`. It reduces duplication of debugging code and makes it easier to remove all your debugging code when you no longer need it. However, it still requires modifying the code and running it in a console where you can inspect the output. Later in this chapter, we will see how we can overcome those difficulties by adding logging to our code.

Using the Python debugger

Another effective way of debugging Python is to use an interactive debugger. The Python standard library module `pdb` provides such a debugger; however, we usually prefer to use the third-party `pdbpp` package. `pdbpp` is a drop-in replacement for `pdb`, with a somewhat friendlier user interface and some handy additional tools, our favorite of which is *sticky mode*, which allows you to see a whole function while you step through its instructions.

There are a few different ways to activate the debugger (if you have the `pdbpp` package installed, it will be loaded instead of the standard `pdb` debugger). The most common approach is to add a call invoking the debugger to your code. This is known as adding a **breakpoint** to the code.

When the code is run and the interpreter reaches the breakpoint, execution is suspended, and you get console access to an interactive debugger session. You can then inspect all the names in the current scope, and step through the program one line at a time. You can also alter data on the fly to change the flow of the program.

As a toy example, suppose we have a program that receives a dictionary and a tuple of keys as input. It then processes the dictionary items with the given keys. The program is raising a `KeyError` because one of the keys is missing from the dictionary. Suppose we cannot control the input (perhaps it comes from a third-party API), but we want to get past the error so that we can verify that our program would behave correctly on valid input. Let us see how we could use the debugger to interrupt the program, inspect and fix the data, and then allow execution to proceed:

```
# pdebugger.py
# d comes from an input that we do not control
d = {"first": "v1", "second": "v2", "fourth": "v4"}
# keys also comes from an input we do not control
keys = ("first", "second", "third", "fourth")

def do_something_with_value(value):
    print(value)

for key in keys:
    do_something_with_value(d[key])

print("Validation done.")
```

As you can see, this code will break when `key` gets the value `"third"`, which is missing from the dictionary. Remember, we're pretending that both `d` and `keys` come from an input source that we cannot control. If we run the code as it is, we get the following:

```
$ python pdebugger.py
v1
v2
Traceback (most recent call last):
  File ".../ch11/pdebugger.py", line 13, in <module>
    do_something_with_value(d[key])
                            ~^^^^^
KeyError: 'third'
```

We see that that `key` is missing from the dictionary, but since every time we run this code, we may get a different dictionary or `keys` tuple, this information does not really help us. We want to inspect and modify the data while the program is running, so let us insert a breakpoint just before the `for` loop. In modern versions of Python, the simplest way of doing this is to call the built-in `breakpoint()` function:

```
breakpoint()
```

Before Python 3.7, you would have needed to import the `pdb` module and call the `pdb.set_trace()` function:

```
import pdb; pdb.set_trace()
```

Note that we have used a semi-colon to separate multiple statements on the same line. PEP 8 discourages this, but it is quite common when setting a breakpoint like this, as there are fewer lines to remove when you no longer need the breakpoint.

The `breakpoint()` function calls `sys.breakpointhook()`, which, in turn, calls `pdb.set_trace()`. You can override the default behavior of `sys.breakpointhook()` by setting the `PYTHONBREAKPOINT` environment variable to point to an alternative function to import and call instead of `pdb.set_trace()`.

The code for this example is in the `pdebugger_pdb.py` module. If we now run this code, things get interesting (note that your output may vary a little and that all the comments in this output were added by us):

```
$ python pdebugger_pdb.py
[0] > .../ch11/pdebugger_pdb.py(17)<module>()
-> for key in keys:
(Pdb++) l
 16
 17 -> for key in keys:  # breakpoint comes in
 18 do_something_with_value(d[key])
 19

(Pdb++) keys  # inspect the keys tuple
('first', 'second', 'third', 'fourth')
(Pdb++) d.keys()  # inspect keys of d
dict_keys(['first', 'second', 'fourth'])
```

```
(Pdb++) d['third'] = 'placeholder'  # add missing item
(Pdb++) c  # continue
v1
v2
placeholder
v4
Validation done.
```

First, note that when you reach a breakpoint, you are served a console that tells you where you are (the Python module) and which line is the next one to be executed. You can, at this point, perform some exploratory actions, such as inspecting the code before and after the next line, printing a stack trace, and interacting with the objects. In our case, we first inspect the `keys` tuple. We also inspect the keys of `d`. We see that `'third'` is missing, so we put it in ourselves (could this be dangerous? Think about it.). Finally, now that all the keys are in, we type `c` to continue normal execution.

The debugger also gives you the ability to execute your code one line at a time using the `n` command (for next). You can use the `s` command to step into a function for deeper analysis or set additional breakpoints with the `b` command. For a complete list of commands, please refer to the documentation (which you can find at `https://docs.python.org/3.12/library/pdb.html`) or type `h` (for help) in the debugger console.

You can see, from the output of the preceding run, that we could finally get to the end of the validation.

`pdb` (or `pdbpp`) is an invaluable tool that we use every day. So, please experiment with it. Set a breakpoint somewhere and try to inspect it, follow the official documentation, and try the commands in your code to see their effect and learn them well.

Notice that, in this example, we have assumed you installed `pdbpp`. If that is not the case, then you might find that some commands behave a bit differently in plain `pdb`. One example is the letter *d*, which `pdb` interprets as the *down* command. To get around that, you would have to add an `!` in front of `d` to tell `pdb` that it is meant to be interpreted literally, and not as a command.

Inspecting logs

Another way of debugging a misbehaving application is to inspect its logs. A **log** is an ordered list of events that occurred or actions that were taken during the running of an application. If a log is written to a file on disk, it is known as a **log file**.

Using logs for debugging is, in some ways, similar to adding `print()` calls or using a custom debug function. The key difference is that we typically add logging to our code from the start to aid future debugging, rather than adding it during debugging and then removing it again. Another difference is that logging can easily be configured to output to a file or a network location. These two aspects make logging ideal for debugging code that is running on a remote machine that you might not have direct access to.

The fact that logging is usually added to the code before a bug has occurred does pose the challenge of deciding what to log. We would typically expect to find entries in the logs corresponding to the start and completion (and potentially also intermediate steps) of any important process that takes place within the application. The values of important variables should be included in these log entries. Errors also need to be logged so that if a problem occurs, we can inspect the logs to find out what went wrong.

Nearly every aspect of logging in Python can be configured in various ways. This gives us a lot of power, as we can change where logs are output to, which log messages are output, and how log messages are formatted, simply by changing the logging configuration and without changing any other code. The four main types of objects involved in logging in Python are:

- **Loggers**: Expose the interface that the application code uses directly
- **Handlers**: Send the log records (created by loggers) to the appropriate destination
- **Filters**: Provide a finer-grained facility for determining which log records to output
- **Formatters**: Specify the layout of the log records in the final output

Logging is performed by calling methods on instances of the `Logger` class. Each line you log has a severity level associated with it. The most commonly used levels are `DEBUG`, `INFO`, `WARNING`, `ERROR`, and `CRITICAL`. Loggers use these levels to determine which log messages to output. Anything below the logger's level will be ignored. This means that you must take care to log at the appropriate level. If you log everything at the `DEBUG` level, you will need to configure your logger at (or below) the `DEBUG` level to see any of your messages. This can quickly result in your log files becoming extremely large. A similar problem occurs if you log everything at the `CRITICAL` level.

Python gives you several choices of where to log to. You can log to a file, a network location, a queue, a console, your operating system's logging facilities, and so on. Where you send your logs will typically depend very much on the context. For example, when you run your code in your development environment, you will typically log to your terminal. If your application runs on a single machine, you might log to a file or send your logs to the operating system's logging facilities.

On the other hand, if your application uses a distributed architecture that spans multiple machines (such as in the case of service-oriented or microservice architectures), it is better to implement a centralized solution for logging so that all log messages coming from each service can be stored and investigated in a single place. This makes debugging much easier because trying to correlate giant files from multiple sources to figure out what went wrong can become truly challenging.

A **service-oriented architecture (SOA)** is an architectural pattern in software design in which application components provide services to other components via a communications protocol, typically over a network. The beauty of this system is that, when coded properly, each service can be written in the most appropriate language to serve its purpose. The only thing that matters is the communication with the other services, which needs to happen via a common format so that data exchange can be done.

Microservice architectures are an evolution of SOAs but follow a different set of architectural patterns.

The downside of the configurability of Python's logging is that the logging machinery is somewhat complex. Fortunately, the defaults are often sufficient, and you only need to override settings when you have a specific need for customization. Let us see a simple example of logging a few messages to a file:

```
# log.py
import logging

logging.basicConfig(
    filename="ch11.log",
    level=logging.DEBUG,
    format="[%(asctime)s] %(levelname)s: %(message)s",
    datefmt="%m/%d/%Y %I:%M:%S %p")

mylist = [1, 2, 3]
logging.info("Starting to process 'mylist'...")

for position in range(4):
    try:
        logging.debug(
            "Value at position %s is %s",
```

```
            position,
            mylist[position]
        )
    except IndexError:
        logging.exception("Faulty position: %s", position)

logging.info("Done processing 'mylist'.")
```

First, we import the `logging` module, then we set up a basic configuration. We specify a filename, configure the logger to output any log messages with the level `DEBUG` or higher, and set the message format. We want to log the date and time information, the level, and the message.

With the configuration in place, we can start logging. We start by logging an `info` message that tells us we are about to process our list. Inside the loop, we will log the value at each position (we use the `debug()` function to log at the `DEBUG` level). We use `debug()` here so that we can filter out these logs in the future (by configuring the logger's `level` to `logging.INFO` or more) because we might have to handle large lists, and we do not want to always log all the values.

If we get `IndexError` (and we do, since we are looping over `range(4)`), we call `logging.exception()`, which logs at the `ERROR` level, but also outputs the exception traceback.

At the end of the code, we log another `info` message to say that we are done. After running this code, we will have a new `ch11.log` file with the following content:

```
# ch11.log
[10/06/2024 10:08:04 PM] INFO: Starting to process 'mylist'...
[10/06/2024 10:08:04 PM] DEBUG: Value at position 0 is 1
[10/06/2024 10:08:04 PM] DEBUG: Value at position 1 is 2
[10/06/2024 10:08:04 PM] DEBUG: Value at position 2 is 3
[10/06/2024 10:08:04 PM] ERROR: Faulty position: 3
Traceback (most recent call last):
  File ".../ch11/log.py", line 20, in <module>
    mylist[position],
    ~~~~~~^^^^^^^^^^
IndexError: list index out of range
[10/06/2024 10:08:04 PM] INFO: Done processing 'mylist'.
```

This is precisely what we need to be able to debug an application that is running on a remote machine, rather than our own development environment. We can see what our code did, the traceback of any exception raised, and so on.

Feel free to modify the logging levels in the previous example, both the code and the configuration. This way, you'll be able to see how the output changes according to your setup.

The example presented here only scratches the surface of logging. For a more in-depth explanation, you can find information in the *Python HOWTOs* section of the official Python documentation: *Logging HOWTO* and *Logging Cookbook*.

Logging is an art. You need to find a good balance between logging everything and logging nothing. Ideally, you should log anything that you need to make sure your application is working correctly, and possibly all errors or exceptions.

Other techniques

We will end this section on debugging by briefly mentioning a couple of other techniques that you may find useful.

Reading tracebacks

Bugs often manifest as unhandled exceptions. The ability to interpret an exception traceback is therefore a crucial skill for successful debugging. Make sure that you have read and understood the section on tracebacks in *Chapter 7*, *Exceptions and Context Managers*. If you are trying to understand why an exception happened, it is often useful to inspect the state of your program (using the techniques we discussed above) at the lines mentioned in the traceback.

Assertions

Bugs are often the result of incorrect assumptions in our code. Assertions can be helpful for validating those assumptions. If our assumptions are valid, the assertions pass and execution proceeds normally. If they are not, we get an exception telling us which of our assumptions are incorrect. Sometimes, instead of inspecting with a debugger or `print()` statements, it is quicker to drop a couple of assertions in the code just to exclude possibilities. Let us see an example:

```
# assertions.py
mylist = [1, 2, 3]  #  pretend this comes from an external source
assert 4 == len(mylist)  # this will break
for position in range(4):
    print(mylist[position])
```

In this example, we pretend that `mylist` comes from some external source that we do not control (maybe user input). The `for` loop assumes that `mylist` has four elements and we have added an assertion to validate that assumption. When we run the code, the result is this:

```
$ python assertions.py
Traceback (most recent call last):
  File ".../ch11/assertions.py", line 4, in <module>
    assert 4 == len(mylist)  # this will break
           ^^^^^^^^^^^^^^^^
AssertionError
```

This tells us exactly where the problem is.

Running a program with the `-O` flag active will cause Python to ignore all assertions. This is something to keep in mind if our code depends on assertions to work.

Assertions also allow for a longer format that includes a second expression, such as:

```
assert expression1, expression2
```

The second expression is passed to the `AssertionError` exception raised by the statement. It is typically a string with an error message. For example, if we changed the assertion in the last example to the following:

```
assert 4 == len(mylist), f"Mylist has {len(mylist)} elements"
```

the result would be:

```
$ python assertions.py
Traceback (most recent call last):
  File ".../ch11/assertions.py", line 19, in <module>
    assert 4 == len(mylist), f"Mylist has {len(mylist)} elements"
           ^^^^^^^^^^^^^^^^
AssertionError: Mylist has 3 elements
```

Where to find information

The official Python documentation contains a section dedicated to debugging and profiling. There, you can read about the `bdb` debugger framework and about modules such as `faulthandler`, `timeit`, `trace`, `tracemalloc`, and `pdb`.

Let us now explore some troubleshooting guidelines.

Troubleshooting guidelines

In this short section, we would like to give you a few tips that come from our troubleshooting experience.

Where to inspect

Our first suggestion concerns where to place your debugging breakpoints. Regardless of whether you are using `print()`, a custom function, `pdb`, or logging, you still have to choose where to place the calls that provide you with the information. Some places are definitely better than others, and there are ways to handle the debugging progression that are better than others.

We normally avoid placing a breakpoint inside an `if` clause. If the branch containing the breakpoint is not executed, we lose the chance to get the information we want. Sometimes, it can be difficult to reproduce a bug, or it may take a while for your code to reach the breakpoint, so think carefully before placing them.

Another important thing is where to start. Imagine that you have 100 lines of code that handle your data. Data comes in at line 1, and somehow, it is wrong at line 100. You do not know where the bug is, so what do you do? You can place a breakpoint at line 1 and patiently step through all 100 lines, checking your data at every step. In the worst-case scenario, 99 lines (and many cups of coffee) later, you spot the bug. So, consider using a different approach.

Start at line 50 and inspect. If the data is good, it means the bug happens later, in which case you place your next breakpoint at line 75. If the data at line 50 is already bad, you go on by placing a breakpoint at line 25. Then, you repeat. Each time, you move either backward or forward, by half the jump you did last time.

In our worst-case scenario, your debugging would go from 1, 2, 3, ..., 99, in a linear fashion, to a series of jumps such as 50, 75, 87, 93, 96, ..., 99, which is much faster. In fact, it is logarithmic. This searching technique is called **binary search**; it is based on a divide-and-conquer approach, and it is highly effective, so try to master it.

Using tests to debug

In *Chapter 10*, *Testing*, we briefly introduced you to **test-driven development** (**TDD**). One TDD practice that you really should adopt, even if you do not subscribe to TDD as a whole, is writing tests that reproduce a bug before you start changing your code to fix the bug. There are several reasons for this. If you have a bug and all tests are passing, it means something is wrong or missing in your test code base.

Adding these tests will help you ensure that you really do fix the bug: the tests should only pass if the bug is gone. Finally, having these tests will protect you from inadvertently reintroducing the same bug again.

Monitoring

Monitoring is also important. Software applications can sometimes behave in unexpected ways in edge-case situations, such as the network being down, a queue being full, or an external component being unresponsive. In these cases, it is important to have an idea of what the big picture was when the problem occurred and be able to correlate it to something related to it in a subtle, perhaps mysterious, way.

You can monitor API endpoints, processes, web pages' availability and load times, and everything that you can code. In general, when starting an application from scratch, it can be helpful to think about how you want to monitor it from the earliest design stages.

Now, let us move on to see how we can profile Python code.

Profiling Python

Profiling means having the application run while keeping track of several different parameters, such as the number of times a function is called, and the amount of time spent inside it.

Profiling is closely related to debugging. Although the tools and processes used are quite different, both activities involve probing and analyzing your code to understand where the root of a problem lies, and then making changes to fix it. The difference is that instead of incorrect output or crashing, the problem we are trying to solve is poor performance.

Sometimes, profiling will point to where the performance bottleneck is, at which point you will need to use the debugging techniques we discussed earlier in this chapter to understand why a particular piece of code does not perform as well as it should. For example, faulty logic in a database query might result in loading thousands of rows from a table instead of just hundreds. Profiling might show you that a particular function is called many more times than expected, at which point you would need to use your debugging skills to work out why that is and address the problem.

There are a few ways to profile a Python application. If you look at the Profiling section in the standard library official documentation, you will see that there are two different implementations of the same profiling interface, `profile` and `cProfile`:

- `cProfile` is written in C and adds comparatively little overhead, which makes it suitable for profiling long-running programs.
- `profile` is implemented in pure Python and, as a result, adds significant overhead to profiled programs.

This interface does **deterministic profiling**, which means that all function calls, function returns, and exception events are monitored, and precise timings are made for the intervals between these events. Another approach, called **statistical profiling**, randomly samples the program's call stack at regular intervals and deduces where time is being spent.

The latter usually involves less overhead but provides only approximate results. Moreover, because of the way the Python interpreter runs the code, deterministic profiling does not add as much overhead as one would think, so we will show you a simple example using `cProfile` from the command line.

There are situations where even the relatively low overhead of `cProfile` is not acceptable, for example, if you need to profile code on a live production web server because you cannot reproduce the performance problem in your development environment. For such cases, you really do need a statistical profiler. If you are interested in statistical profiling for Python, we suggest you look at `py-spy` (`https://github.com/benfred/py-spy`).

We are going to calculate Pythagorean triples again, using the following code:

```
# profiling/triples.py
def calc_triples(mx):
    triples = []
    for a in range(1, mx + 1):
        for b in range(a, mx + 1):
            hypotenuse = calc_hypotenuse(a, b)
            if is_int(hypotenuse):
                triples.append((a, b, int(hypotenuse)))
    return triples

def calc_hypotenuse(a, b):
    return (a**2 + b**2) ** 0.5

def is_int(n):
```

```
    return n.is_integer()

triples = calc_triples(1000)
```

The script is simple; we iterate over the interval `[1, mx]` with `a` and `b` (avoiding repetition of pairs by setting `b >= a`) and we check whether they belong to a right triangle. We use `calc_hypotenuse()` to get `hypotenuse` for `a` and `b`, and then, with `is_int()`, we check whether it is an integer, which means `(a, b, hypotenuse)` is a Pythagorean triple.

When we profile this script, we get information in a tabular form. The columns are `ncalls` (the number of calls to the function), `tottime` (the total time spent in each function), `percall` (the average time spent in each function per call), `cumtime` (the cumulative time spent in a function plus all functions it calls), `percall` (the average cumulative time spent per call), and `filename:lineno(function)`. Here is the result we got (to save space, we are omitting the two `percall` columns):

```
$ python -m cProfile profiling/triples.py
1502538 function calls in 0.393 seconds
Ordered by: cumulative time

ncalls tottime cumtime filename:lineno(function)
     1   0.000   0.393 {built-in method builtins.exec}
     1   0.000   0.393 triples.py:1(<module>)
     1   0.143   0.393 triples.py:1(calc_triples)
500500   0.087   0.147 triples.py:15(is_int)
500500   0.102   0.102 triples.py:11(calc_hypotenuse)
500500   0.060   0.060 {method 'is_integer' of 'float' objects}
  1034   0.000   0.000 {method 'append' of 'list' objects}
     1   0.000   0.000 {method 'disable' of '_lsprof.Profiler' objects}
```

Even with this limited amount of data, we can still infer some useful information about this code. First, we can see that the time complexity of the algorithm we have chosen grows with the square of the input size. The number of calls to `calc_hypotenuse()` is exactly *mx (mx + 1) / 2*. We ran the script with `mx = 1000`, and we got exactly 500,500 calls. Three main things happen inside the loop: we call `calc_hypotenuse()`, we call `is_int()`, and, if the condition is met, we append it to the `triples` list.

Taking a look at the cumulative times in the profiling report, we notice that the program spent 0.147 seconds inside `is_int()`, compared to 0.102 seconds spent inside `calc_hypotenuse()`. These functions were called the same number of times, so our first target for optimization should be the more expensive `is_int()`.

If we look at the `tottime` column, we see that the program spent 0.087 seconds in `is_int()`. This excludes the 0.060 seconds spent in calls from `is_int()` to the `is_integer()` method of `float` objects. However, `is_int()` does not do anything other than call the `is_integer()` method of its parameter `n`. This means that just the additional function call adds an overhead of 87 milliseconds. In this program, there is not much benefit to having the `is_int()` function, so we can gain 87 milliseconds by just calling `hypotenuse.is_integer()` directly instead.

If we rerun the profiling, we see that we now spend more time in `calc_hypotenuse()` than in the `is_integer()` method. Let us see if we can improve that as well. As we mentioned in *Chapter 5*, *Comprehensions and Generators*, using the `**` power operator to calculate the square of a number is more expensive than multiplying it by itself. With that in mind, we can try to improve performance by changing `calc_hypotenuse()` to the following:

```
def calc_hypotenuse(a, b):
    return (a * a + b * b) ** 0.5
```

After rerunning the profiling again, we find that the program now spends 0.084 seconds in the `calc_hypotenuse()` function. We have gained only 18 milliseconds. We could potentially gain more by eliminating the overhead of the call to `calc_hypotenuse()` and calculating the hypotenuse directly:

```
            hypotenuse = (a * a + b * b) ** 0.5
```

Profiling this version shows that we can gain up to 100 milliseconds in this way. However, we think that, in this case, the benefits of readability, maintainability, and testability that the function gives us outweigh the performance improvement of removing it.

You will find all four versions of this program in the source code for the book. We encourage you to run the profiling yourself and experiment with other changes to the code to see what impact they have on performance (for example, you could try to convert `calc_triples()` into a generator function).

This example was trivial, of course, but enough to show you how you could profile an application. Having the number of calls that are made to a function helps us better understand the time complexity of our algorithms. For example, many coders fail to see that those two `for` loops run proportionally to the square of the input size.

We have seen profiling of functions, but it is also possible to go to an even higher level of granularity and profile each line of a piece of code, if necessary. The average Python programmer will not need to do much profiling in their career, but it might happen, so it is good to know the options we have.

One thing to mention: the results of profiling will quite likely differ depending on what system you are running on. Therefore, it is important to be able to profile software on a system that is as close as possible to the one the software is deployed on, if not actually on it.

In this section, we have focused on profiling and optimizing the running time of a program. Profiling can also be used to analyze and optimize memory usage. One of the most popular tools for memory profiling in Python is memray. You can read more about it at `https://bloomberg.github.io/memray/`.

When to profile

It is important to know when it is appropriate to profile, and what to do with the results we get. Donald Knuth once said, "*Premature optimization is the root of all evil*," and, although we wouldn't have put it quite so strongly, we do agree with him. For example, it is seldom worth sacrificing readability or maintainability for the sake of gaining a few milliseconds in speed.

Your primary concern should always be *correctness*. You want your code to deliver the correct results, therefore write tests, find edge cases, and stress your code in every way you think makes sense. Do not be protective; do not put things in the back of your brain for later because you think they are not likely to happen. Be thorough.

Second, take care of coding *best practices*. Remember the following: readability, extensibility, loose coupling, modularity, and design. Apply OOP principles: encapsulation, abstraction, single responsibility, open/closed, and so on. Read up on these concepts. They will open horizons for you, and they will expand the way you think about code.

Third, *refactor*. The Boy Scouts rule says:

> *Always leave the campground cleaner than you found it.*

Apply this rule to your code.

Finally, when all of this has been taken care of, then and only then take care of optimizing and profiling.

Run your profiler and identify bottlenecks. When analyzing the profiling results, focus on the functions that were called the most. As we mentioned in *Chapter 5*, *Comprehensions and Generators*, you will often gain more from even a small improvement to a function that is called a million times than from trying to improve a function that is only called a few times. When you have an idea of the bottlenecks you need to address, start with the worst one first. Sometimes, fixing a bottleneck causes a ripple effect that will expand and change the way the rest of the code works. Sometimes, this is only a little, and sometimes, it is a bit more, depending on how your code was designed and implemented. Therefore, start with the biggest issue first.

One of the reasons Python is so popular is that it is possible to extend it with modules written in faster, compiled languages like C or C++. So, if you have some critical piece of code and you simply cannot achieve the performance you need in pure Python, you always have the option of rewriting part of it in C.

Measuring execution time

Before we finish this chapter, we want to briefly touch on the topic of measuring the execution time of code. Sometimes, it is helpful to measure the performance of small pieces of code to compare their performance. For example, if you have different ways of implementing some operation and you really need the fastest version, you may want to compare their performance without profiling your entire application.

We have already seen some examples of measuring and comparing execution times earlier in this book, for example, in *Chapter 5*, *Comprehensions and Generators*, when we compared the performance of `for` loops, list comprehensions, and the `map()` function. At this point, we would like to introduce you to a better approach, using the `timeit` module. This module uses techniques such as timing many repeated executions of the code to improve measurement accuracy.

The `timeit` module can be a bit tricky to use. We recommend that you read about it in the official Python documentation and experiment with the examples there until you understand how to use it. Here, we will just give a brief demonstration of using the command-line interface to time our two different versions of `calc_hypotenuse()` from the previous example:

```
$ python -m timeit -s 'a=2; b=3' '(a**2 + b**2) ** .5'
5000000 loops, best of 5: 91 nsec per loop
```

Here, we are running the `timeit` module, initializing variables `a = 2` and `b = 3`, before timing the execution of `(a**2 + b**2) ** .5`. In the output, we can see that `timeit` ran 5 repetitions timing 5,000,000 loop iterations executing our calculation. Out of those 5 repetitions, the best average execution time over 5,000,000 iterations was 91 nanoseconds. Let us see how the alternative calculation, `(a*a + b*b) ** .5`, performs:

```
$ python -m timeit -s 'a=2; b=3' '(a*a + b*b) ** .5'
5000000 loops, best of 5: 72.8 nsec per loop
```

This time, we get an average of 72.8 nanoseconds per loop. This confirms again that the second version is slightly faster.

The `timeit` module automatically chooses the number of iterations to ensure the total running time is at least 0.2 seconds. This helps to improve accuracy by reducing the relative impact of measurement overhead.

For further information about measuring Python performance, make sure you check out `pyperf` (`https://github.com/psf/pyperf`) and `pyperformance` (`https://github.com/python/pyperformance`).

Summary

In this short chapter, we looked at different techniques and suggestions for debugging, troubleshooting, and profiling our code. Debugging is an activity that is always part of a software developer's work, so it is important to be good at it.

If approached with the correct attitude, it can be fun and rewarding.

We explored techniques to inspect our code using custom functions, logging, debuggers, traceback information, profiling, and assertions. We saw simple examples of most of them. We also discussed some guidelines that will help when it comes to facing the fire.

Remember always to *stay calm and focused*, and debugging will be much easier. This, too, is a skill that needs to be learned and it is the most important. An agitated and stressed mind cannot work properly, logically, and creatively. Therefore, if you do not strengthen it, it will be difficult for you to put all your knowledge to good use. So, when facing a difficult bug, if you have the opportunity, make sure you go for a short walk or take a power nap—relax. Often, the solution presents itself after a good break.

In the next chapter, we are going to explore type hinting and the use of static type checkers, which can be useful for reducing the likelihood of certain types of bugs.

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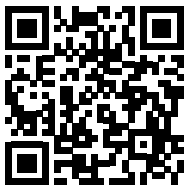

12

Introduction to Type Hinting

> *"Knowing yourself is the beginning of all wisdom."*
>
> *– Aristotle*

In this chapter, we are going to explore the topic of **type hinting**. Type hinting is perhaps the biggest change introduced in Python since Python 2.2, which saw the unification of types and classes.

Specifically, we will study the following topics:

- Python approach to types.
- Types available for annotations.
- Protocols (in brief).
- Mypy, a static type checker for Python.

Python approach to types

Python is both a **strongly typed** and a **dynamically typed** language.

Strongly typed means that Python does not allow implicit type conversions that could lead to unexpected behaviors. Consider the following **php** code:

```php
<?php
$a = 2;
$b = "2";
echo $a + $b; // prints: 4
?>
```

In php, variables are prepended with a $ sign. In the above code, we set `$a` to the integer number 2, and `$b` to the string `"2"`. To add them together, php performs an implicit conversion of `$b`, from string to integer. This is referred to as **type juggling**. This might seem a convenient feature, but the fact that php is weakly typed has the potential to lead to bugs in the code. If we tried to do the same in Python, the result would be much different:

```
# example.strongly.typed.py
a = 2
b = "2"
print(a + b)
```

Running the above produces:

```
$ python ch12/example.strongly.typed.py
Traceback (most recent call last):
  File "ch12/example.strongly.typed.py", line 3, in <module>
    print(a + b)
          ~~^~~
TypeError: unsupported operand type(s) for +: 'int' and 'str'
```

Python is strongly typed, so when we try to add an integer to a string – or any pair of incompatible types – we get `TypeError`.

Dynamically typed means that Python determines the type of a variable at runtime, which means that we do not specify types explicitly in the code.

In contrast, languages like C++, Java, C#, and Swift are all **statically typed**. When we declare variables in these languages, we must specify their type. For example, in Java, it is common to see variables declared like this:

```
String name = "John Doe";
int age = 60;
```

There are pros and cons to both approaches, so it's hardly a matter of which is best. Python was designed to be concise, lean, and elegant. One of the advantages of its design is known as **duck typing**.

Duck typing

Another concept that Python helped popularize is **duck typing**. In essence, this means that the type or class of an object is less important than the methods it defines or the operations it supports. As the saying goes: *"If it looks like a duck, swims like a duck, and quacks like a duck, then it probably is a duck."*

Duck typing is used extensively in Python because the language is dynamically typed. It allows for greater flexibility and code reuse. Consider the following example:

```
# duck_typing.py
class Circle:
    def __init__(self, radius):
        self.radius = radius

    def area(self):
        return 3.14159 * (self.radius**2)

class Rectangle:
    def __init__(self, width, height):
        self.width = width
        self.height = height

    def area(self):
        return self.width * self.height

def print_shape_info(shape):
    print(f"{shape.__class__.__name__} area: {shape.area()}")

circle = Circle(5)
rectangle = Rectangle(4, 6)

print_shape_info(circle)  # Circle area: 78.53975
print_shape_info(rectangle)  # Rectangle area: 24
```

In the above code, the `print_shape_info()` function does not care about the specific type of `shape`. It only cares that `shape` has a method called `area()`.

History of type hinting

Although Python's approach to types is one of the features that contributed to the success of its wide adoption, in Python 3, we saw the beginning of a gradual and carefully designed evolution toward the integration of type safety features that still maintained Python's dynamic nature.

This began in Python 3.0, with the introduction of function annotations, through PEP 3107 (`https://peps.python.org/pep-3107/`). This addition allowed developers to add arbitrary metadata to function parameters and return values. These annotations were initially intended as a tool for documentation and had no semantic meaning. This step was the foundation layer that allowed the introduction of the explicit support of type hinting.

In Python 3.5, with the landing of PEP 484 (`https://peps.python.org/pep-0484/`), the real inception of type hinting came about. PEP 484 formalized the addition of type hints, building on the syntax laid out by PEP 3107. It defined a standard way to declare types for function parameters, return values, and variables.

This enabled optional static type checking, and developers could now use tools like **Mypy** to detect type-related errors before runtime.

In Python 3.6, we saw the introduction of annotations for variable declarations. This was brought by PEP 526 (`https://peps.python.org/pep-0526/`). This new addition meant that types could be explicitly declared throughout the code, and not just in functions. It included class attributes and module-level variables as well. This further improved Python's type hinting capabilities and made it easier to statically analyze code.

Subsequent enhancements and PEPs refined and expanded Python's type system even further. The main ones were the following:

- PEP 544 (`https://peps.python.org/pep-0544/`) landed in Python 3.8 and introduced the concept of protocols, which enabled duck typing and further static type checking.
- PEP 585 (`https://peps.python.org/pep-0585/`) landed in Python 3.9 and set another milestone. It revolutionized type hinting by integrating it directly with Python core collections. This removed the need to import types from the `typing` module for common data structures, such as dictionaries and lists.
- PEP 586 (`https://peps.python.org/pep-0586/`) landed in Python 3.8 and added literal types, allowing functions to specify literal values as parameters.
- PEP 589 (`https://peps.python.org/pep-0589/`) landed in Python 3.8 and introduced `TypedDict`, which enabled precise type hints for dictionaries with a fixed set of keys.
- PEP 604 (`https://peps.python.org/pep-0604/`) landed in Python 3.10 and introduced a simplification of the syntax for union types, which streamlined annotations and improved the readability of the code.

Other notable PEPs are:

- PEP 561 (`https://peps.python.org/pep-0561/`), which specifies how to distribute packages that support type checking.
- PEP 563 (`https://peps.python.org/pep-0563/`), which changed the evaluation of annotations such that they are not evaluated at function definition time. This postponement was made the default behavior in Python 3.10.
- PEP 593 (`https://peps.python.org/pep-0593/`), which introduced a way to augment existing type hints with arbitrary metadata, potentially for use by third-party tools.
- PEP 612 (`https://peps.python.org/pep-0612/`), which introduced parameter specifications, which allow more complex types of variable annotations, particularly useful for decorators that modify function signatures.
- PEP 647 (`https://peps.python.org/pep-0647/`), which introduced type guards, functions that enable more precise type inference in conditional blocks.
- PEP 673 (`https://peps.python.org/pep-0673/`), which introduced the `Self` type to represent the instance type within class bodies and method returns, making type hints involving classes more expressive and accurate.

The evolution of type hinting in Python has been driven by the desire for greater robustness and scalability of code, leveraging the power of Python's dynamic nature.

Although Python's type hinting popularity seems to continuously increase, it is important to note that, according to the authors of PEP 484 (Guido van Rossum, Jukka Lehtosalo, and Łukasz Langa):

> *"Python will remain a dynamically typed language, and the authors have no desire to ever make type hints mandatory, even by convention."*

The way in which Python's type hinting has been introduced, and the philosophical approach of this PEP's authors and Python's lead developers, suggest that the choice of using type hinting is, and always will be, up to the developer.

Let us now see some of the main benefits of type hinting.

Benefits of type hinting

Adopting type hinting brings several key benefits, such as enhanced code quality, maintainability, and improved developer efficiency. We can summarize them in a list:

- **Improved code readability and documentation**: Type hints are a form of documentation. They clarify the type of arguments a function expects, and what type it returns. This helps developers understand the code immediately, with no need to read long comments or much code.
- **Enhanced error detection**: Static type checkers, such as Mypy, can scan the codebase and flag errors before runtime. This means that some bugs can be eliminated before they become a problem.
- **Better IDE experience and autocompletion**: Modern IDEs leverage type hints to provide better autocompletion and enhanced refactoring capabilities. Moreover, with type hints, the IDE can suggest appropriate methods and attributes for an object.
- **Improved collaboration and code reviews**: The documenting quality of type hints makes it easier to understand the code at a glance, which, for example, can be useful when reading changes in a pull request.
- **Code flexibility and reusability**: Python's type hinting includes features such as generics, custom types, and protocols, which help developers write better-structured, more flexible code.

Another important aspect of Python's type hinting system is that it can be introduced gradually. It is, in fact, quite common to introduce type hints progressively in a codebase, initially limiting efforts to where it matters most.

Type annotations

Now that we have a foundational understanding of Python's dynamic nature and its approach to type hinting, let us start exploring some examples and concepts to see how it is applied in practice.

While we expose the main types we can use to annotate our code, you might find slight differences with what you are used to, if you have previously used type annotations in your code. This is likely because type hinting in Python is currently still evolving, so it is different according to which Python version you are using. In this chapter, we will stick to the rules for Python 3.12.

Let us start with a basic example.

Annotating functions

In Python, we can annotate both function parameters and their return values. Let us start with a basic `greeter` function:

```
# annotations/basic.py
def greeter(name):
    return f"Hello, {name}!"
```

This is a simple Python function that takes a `name` and returns a greeting. We can now annotate the function to specify that we expect `name` to be a string and that the greeting returned will also be a string.

```
# annotations/basic.py
def greeter_annotated(name: str) -> str:
    return f"Hello, {name}!"
```

As you can see from the highlighted section in this code, the syntax to annotate a function is simple. We specify the type using a colon after the parameter name. The `return` value is annotated with an arrow (`->`) followed by the type of the object returned.

Let us now add another parameter, `age`, which we expect to be an integer.

```
# annotations/basic.py
def greeter_annotated_age(name: str, age: int) -> str:
    return f"Hello, {name}! You are {age} years old."
```

As you probably expected, we simply did the same for the `age` parameter, only, this time, we specified `int`, instead of `str`.

If you use a relatively modern IDE, try out this code. If you type either `name` or `age` and then a dot (`.`), the editor should suggest only the methods and attributes that are pertinent to the type of object you are using.

This was a basic example designed to show you the syntax of type annotations. Please disregard the artificial names, such as `greeter_annotated()` and `greeter_annotated_age()`; they are not good names, but they should help you spot the differences more quickly.

We are now going to expand on this, to show you the real capabilities of Python type hinting.

The Any type

This is a special kind of type. Any function without a return type, or parameter type, will implicitly default to using `Any`. Therefore, the following function declarations are equivalent.

```
# annotations/any.py
from typing import Any

def square(n):
    return n**2

def square_annotated(n: Any) -> Any:
    return n**2
```

The above declarations are completely equivalent. `Any` can be useful in certain circumstances, such as when annotating data containers, function decorators, or when a function is designed to handle inputs of multiple types. A simple example could be:

```
# annotations/any.py
from typing import Any
def reverse(items: list) -> list:
    return list(reversed(items))

def reverse_any(items: list[Any]) -> list[Any]:
    return list(reversed(items))
```

In this case, the two definitions are again completely equivalent. The only difference is that in the second one, by using `Any`, we explicitly state the list `items` is expected to contain *any* kind of object.

Type aliases

We can use almost any Python type in type hints. Moreover, the `typing` module introduced several constructs that we can leverage to expand on them.

One such construct is **type aliases**, which are defined using a `type` statement. The result is an instance of `TypeAliasType`. They are a convenient way to simplify how the code reads. Let us see an example:

```
# annotations/type.aliases.py
type DatabasePort = int

def connect_to_database(host: str, port: DatabasePort):
```

```
    print(f"Connecting to {host} on port {port}...")
```

As we can see in the above example, we can define our own type aliases. From the perspective of a static type checker, `DatabasePort` and `int` will be treated equivalently.

Although it might not be evident from such a dummy example, using a type alias enhances readability and simplifies refactoring. Imagine several functions expecting `DatabasePort`: if we wanted to refactor the codebase to represent a port using a string, we would just need to change the line in which we define `DatabasePort`. Had we simply used `int` instead, we would need to refactor all function definitions.

Special forms

Special forms can be used as types in annotations. They all support subscription using [], but each has a unique syntax. Here, we are going to see `Optional` and `Union`; for the complete list of all special forms, please refer to the official documentation at `https://docs.python.org/3/library/typing.html#special-forms`.

Optional

Python allows optional arguments when a function parameter has a default. Here, we have a distinction to make. Let us bring back the `greeter` function, and add a default value to it:

```
# annotations/optional.py
def greeter(name: str = "stranger") -> str:
    return f"Hello, {name}!"
```

This time, we have added a default value to the `greeter()` function. That means that if we were to call it with no arguments, it would return the string `"Hello, stranger!"`.

This definition assumes that when we call `greeter()`, if we pass `name`, it will be a string. Sometimes, though, this is not what we want, and we require an argument to be `None`, if not provided when the function is called. For situations like this, the `typing` module provides us with the `Optional` special form:

```
# annotations/optional.py
def greeter_optional(name: Optional[str] = None) -> str:
    if name is not None:
        return f"Hello, {name}!"
    return "No-one to greet!"
```

In the `greeter_optional()` function, we don't want to return a greeting when we don't pass a name. Because `None` is not a string, we mark `name` as optional and set its default value to `None`.

Union

Sometimes, an argument can be of different types. For example, when connecting to a database, the port can be specified as either an integer or a string. In these cases, it is useful to have the `Union` special form:

```
# annotations/union.py
from typing import Union

def connect_to_database(host: str, port: Union[int, str]):
    print(f"Connecting to {host} on port {port}...")
```

In the above example, for the `port` parameter, we want to accept both `int` and `str`, and the `Union` special form allows us to do just that.

Since Python 3.10, we don't need to import `Union`, and instead can use a pipe (`|`) to specify a union type.

```
# annotations/union.py
def connect_to_db(host: str, port: int | str):
    print(f"Connecting to {host} on port {port}...")
```

This looks leaner.

`Union`, or its pipe equivalent, incidentally, enables us to avoid having to import `Optional`, since `Optional[str]`, for example, can be written as `Union[str, None]`, or simply `str | None`. Let us see the latter form in an example:

```
# annotations/optional.py
def another_greeter(name: str | None = None) -> str:
    if name is not None:
        return f"Hello, {name}!"
    return "No-one to greet!"
```

Have you noticed that some of the functions defined above have type annotations on their parameters, but nothing for the return value? This is to show you that annotations are completely optional. We could even annotate only some of the parameters a function takes if we wanted to.

Generics

Let us continue our exploration of what is possible to achieve using type hints, by exploring the concept of **generics**.

Say that we wanted to write a `last()` function that takes a list of items, of any kind, and returns the last one, if any, or `None`. We know that all the items in the list are of the same type, but we don't know what type it is. How can we annotate the function properly? The concept of generics helps us do that. The syntax is only a tad more extravagant than what we have seen till now, but it is not that complicated. Let us write that function:

```
# annotations/generics.py
def last[T](items: list[T]) -> T | None:
    return items[-1] if items else None
```

Pay particular attention to the highlighted sections in the code above. First, we need to add a `[T]` as a suffix to the function's name. Then, we can specify that `items` is a list of objects whose type is `T`, whatever that might be. Finally, we can also use `T` for the return value, although, in this case, we have specified the return type to be the union of `T` and `None`, to cater for the edge case in which `items` would be empty.

Even though the function signature is using the generic syntax, you would call it like this: `last([1, 2, 3])`.

Syntactic support for generics is new to Python 3.12. Before that, to achieve the same result, one would have resorted to using the `TypeVar` factory, like this:

```
# annotations/generics.py
from typing import TypeVar
U = TypeVar("U")

def first(items: list[U]) -> U | None:
    return items[0] if items else None
```

Notice that `first()` is not defined as `first[U](…)` in this case.

Thanks to the enhancements in the syntax of Python 3.12, the use of generics is now simpler.

Annotating variables

Let us now take a little detour from functions and discuss variable annotations. We can quickly show you an example that will not require much of an explanation:

```
# annotations/variables.py
x: int = 10
x: float = 3.14
x: bool = True
x: str = "Hello!"
x: bytes = b"Hello!"

# Python 3.9+
x: list[int] = [7, 14, 21]
x: set[int] = {1, 2, 3}
x: dict[str, float] = {"planck": 6.62607015e-34}

# Python 3.8 and earlier
from typing import List, Set, Dict
x: List[int] = [7, 14, 21]
x: Set[int] = {1, 2, 3}
x: Dict[str, float] = {"planck": 6.62607015e-34}

# Python 3.10+
x: list[int | str] = [0, 1, 1, 2, "fibonacci", "rules"]

# Python 3.9 and earlier
from typing import Union
x: list[Union[int, str]] = [0, 1, 1, 2, "fibonacci", "rules"]
```

In the code above, we have declared x to be many things, as an example. As you can see, the syntax is simple: we declare the name of the variable, its type (after the colon), and its value (after the equal sign). We also have provided you with a few examples of how one had to annotate variables in earlier versions of Python. Quite conveniently, in Python 3.12, we can use built-in types directly without having to import much from the `typing` module.

Annotating containers

The typing system assumes that all elements in Python containers will be of the same type. This is true for most containers. For example, consider the following code:

```
# annotations/containers.py

# The type checker assumes all elements of the list are integers
a: list[int] = [1, 2, 3]

# We cannot specify two types for the elements of the list
# it only accepts a single type argument
b: list[int, str] = [1, 2, 3, "four"]  # Wrong!

# The type checker will infer that all keys in `c` are strings
# and all values are integers or strings
c: dict[str, int | str] = {"one": 1, "two": "2"}
```

As you can see in the code above, `list` expects one type argument. In this context, a union, like `int | str` in the annotation of `c`, still counts as one type. However, the type checker will complain about `b`. This reflects the fact that lists in Python are typically used to store an arbitrary number of items of the same type.

Containers that have elements of the same type are called *homogeneous*.

Notice that, even though the syntax is similar, `dict` expects a type for its keys and one for its values.

Annotating tuples

Unlike most other container types, it is common for tuples to contain a fixed number of items with specific types expected in each position. Tuples containing different types are called *heterogeneous*. Because of this, tuples are treated in a special way by the typing system.

There are three ways to annotate tuple types:

- Tuples of fixed length, which can be further categorized into:
    - Tuples without named fields
    - Tuples with named fields

- Tuples of *arbitrary* length

Fixed-length tuples

Let us see an example of fixed-length tuples, without named fields.

```
# annotations/tuples.fixed.py
# Tuple `a` is assigned to a tuple of length 1,
# with a single string element.
a: tuple[str] = ("hello",)

# Tuple `b` is assigned to a tuple of length 2,
# with an integer and a string element.
b: tuple[int, str] = (1, "one")

# Type checker error: the annotation indicates a tuple of
# length 1, but the tuple has 3 elements.
c: tuple[float] = (3.14, 1.0, -1.0)  # Wrong!
```

In the code above, both `a` and `b` are annotated correctly. However, `c` is incorrect, because the annotation indicates a tuple of length `1`, but `c` is of length `3`.

Tuples with named fields

When tuples have more than one or two fields, or when they are used in several places in the codebase, it can be useful to annotate them using `typing.NamedTuple`. Here is a simple example:

```
# annotations/tuples.named.py
from typing import NamedTuple

class Person(NamedTuple):
    name: str
    age: int

fab = Person("Fab", 48)
print(fab)  # Person(name='Fab', age=48)
print(fab.name)  # Fab
print(fab.age)  # 48
print(fab[0])  # Fab
print(fab[1])  # 48
```

As you can see by the results of the `print()` calls, this is equivalent to declaring a tuple, as we learned in *Chapter 2*, *Built-In Data Types*:

```
# annotations/tuples.named.py
import collections
Person = collections.namedtuple("Person", ["name", "age"])
```

Using `typing.NamedTuple` not only allows us to correctly annotate the tuple but we can even specify default values if we wish:

```
# annotations/tuples.named.py
class Point(NamedTuple):
    x: int
    y: int
    z: int = 0

p = Point(1, 2)
print(p)  # Point(x=1, y=2, z=0)
```

Notice how, in the above code, we didn't specify the third argument when we created `p`, but `z` still got assigned to `0` correctly.

Tuples of arbitrary length

If we want to specify a tuple of arbitrary length in which all elements are of the same type, we can use a specific syntax. This can be useful, for example, when we use tuples as immutable sequences. Let us see a few examples:

```
# annotations/tuples.any.length.py
from typing import Any

# We use the ellipsis to indicate that the tuple can have any
# number of elements.
a: tuple[int, ...] = (1, 2, 3)

# All the following are valid, because the tuple can have any
# number of elements.
a = ()
a = (7,)
a = (7, 8, 9, 10, 11)
```

```
# But this is an error, because the tuple can only have integers
a = ("hello", "world")

# We can specify a tuple that must be empty
b: tuple[()] = ()

# Finally, if we annotate a tuple like this:
c: tuple = (1, 2, 3)
# The type checker will treat it as if we had written:
c: tuple[Any, ...] = (1, 2, 3)
# And because of that, all the below are valid:
c = ()
c = ("hello", "my", "friend")
```

As you can see, there are plenty of ways to annotate a tuple. The choice of how strict you want to be is up to you. Remember to be consistent with the rest of the codebase. Also, be mindful of the value that annotations add to your code. If you are writing a library that is supposed to be published and used by other developers, it might make sense to be quite precise in the annotations. On the other hand, being too strict or restrictive for no good reason can hurt your productivity, especially in situations where such precision is not needed.

Abstract base classes (ABCs)

In older versions of Python, the `typing` module would provide several generic versions of types. For example, lists, tuples, sets, and dictionaries, could be annotated using the generic concrete collections `List`, `Tuple`, `Set`, `Dict`, and so on.

Starting from Python 3.9, these generic collections have been deprecated in favor of their corresponding built-in, which means that, for example, it is possible to annotate a list using `list` itself, without needing `typing.List`.

The documentation also points out that these generic collections should be used to annotate return values, whereas parameters should be annotated using abstract collections. For example, we should use `collections.abc.Sequence` to annotate read-only and mutable sequences, like `list`, `tuple`, `str`, `bytes`, and so on.

This is in line with **Postel's law**, also known as the **robustness principle**, which postulates:

> *"Be conservative in what you send, be liberal in what you accept."*

Be liberal in what you accept means that we should not be too restrictive in the way we annotate parameters. If a function takes a parameter called `items`, and all it does to it is iterate, or access an item based on its position, it makes no difference if `items` is a list or a tuple. Therefore, we should not annotate with `tuple` or `list` but use `collections.abc.Sequence` to allow `items` to be passed either as a tuple or a list.

Imagine a situation where you annotate `items` using `tuple`. After a while, you refactor the code and now `items` is passed as a list. The function now has the wrong annotation, as `items` is no longer a tuple. Had we used `collections.abc.Sequence` instead, the function would not require any fixing, since both `tuple` and `list` would be okay.

Let us see an example:

```
# annotations/collections.abcs.py
from collections.abc import Mapping, Sequence

def average_bad(v: list[float]) -> float:
    return sum(v) / len(v)

def average(v: Sequence[float]) -> float:
    return sum(v) / len(v)

def greet_user_bad(user: dict[str, str]) -> str:
    return f"Hello, {user['name']}!"

def greet_user(user: Mapping[str, str]) -> str:
    return f"Hello, {user['name']}!"
```

The above functions should help clarify things. Take `average_bad()`, for example. If we passed `v` as a tuple, it would disagree with the function annotation we used, which is `list`. On the other hand, `average()` does not suffer from the same issue. And of course, we can follow the same reasoning for `greet_user_bad()` and `greet_user()`.

Going back to Postel's Law, when it comes to return values, it is better to be conservative, which means to be specific. Return values should be precise in indicating what the function returns.

This is quite important, especially for the caller, who needs to know the type of object they will receive when calling the function.

Here is another simple example, from the same file, that should help:

```
# annotations/collections.abcs.py
def add_defaults_bad(
    data: Mapping[str, str]
) -> Mapping[str, str]:
    defaults = {"host": "localhost", "port": "5432"}
    return {**defaults, **data}

def add_defaults(data: Mapping[str, str]) -> dict[str, str]:
    defaults = {"host": "localhost", "port": "5432"}
    return {**defaults, **data}
```

In the two functions above, we simply add some pretend connection defaults to whatever is passed in the `data` argument (provided `"host"` and `"port"` keys are missing in `data`). The `add_defaults_bad()` function specifies `Mapping` as the return type. The problem with this is that it is too generic. Objects such as `dict` and its siblings from the `collections` module, `defaultdict`, `Counter`, `OrderedDict`, `ChainMap`, and `UserDict`, for example, all implement the `Mapping` interface. This makes things quite confusing for the caller.

On the other hand, `add_defaults()` is a better function, in that it specifies precisely the return type: `dict`.

Commonly used ABCs include `Iterable`, `Iterator`, `Collection`, `Sequence`, `Mapping`, `Set`, `MutableSequence`, `MutableMapping`, `MutableSet`, and `Callable`.

Let us see a dummy example with `Iterable`:

```
# annotations/collections.abc.iterable.py
from collections.abc import Iterable

def process_items(items: Iterable) -> None:
    for item in items:
        print(item)
```

All the `process_items()` function needs to do is iterate over `items`; therefore, we use `Iterable` to annotate it.

A more interesting example can be offered for `Callable`:

```
# annotations/collections.abc.iterable.py
from collections.abc import Callable

def process_callback(
    arg: str, callback: Callable[[str], str]
) -> str:
    return callback(arg)

def greeter(name: str) -> str:
    return f"Hello, {name}!"

def reverse(name: str) -> str:
    return name[::-1]
```

Here, we have the `process_callback()` function, which defines a string parameter, `arg`, and a `callback` callable object. We have two functions that follow, whose signature specifies a string parameter in input, and a string object as the return value. Notice how the type annotation for `callback`, which is `Callable[[str], str]`, indicates that the `callback` argument should take one string argument in input and return a string in output. When we call these functions with the following code, we get the output that is indicated in the inline comments.

```
# annotations/collections.abc.iterable.py
print(process_callback("Alice", greeter))  # Hello, Alice!
print(process_callback("Alice", reverse))  # ecilA
```

This concludes our tour of abstract base classes.

Special typing primitives

In the `typing` module, there is also a category of objects called **Special Typing Primitives**, which are quite interesting, and it is useful to know at least the most common of them. We have already seen one example: `Any`.

Other notable examples are:

- `AnyStr`: Used to annotate functions that can accept `str` or `bytes` arguments but cannot allow the two to mix. This is known as a **constrained type variable**, which means that the type can only ever be exactly one of the constraints given. In the case of `AnyStr`, it is either `str` or `bytes`.

- `LiteralString`: A special type that includes only literal strings.
- `Never` / `NoReturn`: Can be used to indicate that a function never returns – for example, it might raise an exception.
- `TypeAlias`: Deprecated in favor of the `type` statement.

Finally, the `Self` type deserves a little more consideration.

The Self type

The `Self` type was added in Python 3.11, and it is a special type used to represent the current enclosed class. Let us see an example:

```
# annotations/self.py
from typing import Self
from collections.abc import Iterable
from dataclasses import dataclass

@dataclass
class Point:
    x: float = 0.0
    y: float = 0.0
    z: float = 0.0

    def magnitude(self) -> float:
        return (self.x**2 + self.y**2 + self.z**2) ** 0.5

    @classmethod
    def sum_points(cls, points: Iterable[Self]) -> Self:
        return cls(
            sum(p.x for p in points),
            sum(p.y for p in points),
            sum(p.z for p in points),
        )
```

In the above code, we have created a simple class, `Point`, which represents a three-dimensional point in space. To show you how to use the `Self` type, we have created a `sum_points()` class method, which takes an iterable, `points`, and produces a `Point` object in return, whose coordinates are the sums of the corresponding coordinates in all the items in `points`.

To annotate the `points` parameter, we pass `Self` to `Iterable`, and we do the same for the return value of the method. Before the introduction of the `Self` type, we would have had to create a unique "self" type variable for every class that needed it. You can find an example of this in the official documentation at `https://docs.python.org/3/library/typing.html#typing.Self`.

Notice that both the `self` and the `cls` parameters have no type annotation by convention.

Let us now move on to see how to annotate variable parameters.

Annotating variable parameters

To annotate variable positional and keyword parameters, we use the same syntax we have seen until now. A quick example is better than any explanation:

```
# annotations/variable.parameters.py
def add_query_params(
    *urls: str, **query_params: str
) -> list[str]:
    params = "&".join(f"{k}={v}" for k, v in query_params.items())
    return [f"{url}?{params}" for url in urls]

urls = add_query_params(
    "https://example1.com",
    "https://example2.com",
    "https://example3.com",
    limit="10",
    offset="20",
    sort="desc",
)
print(urls)
# ['https://example1.com?limit=10&offset=20&sort=desc',
#  'https://example2.com?limit=10&offset=20&sort=desc',
#  'https://example3.com?limit=10&offset=20&sort=desc']
```

In the above example, we have written a dummy function, `add_query_params()`, that adds some query parameters to a collection of URLs. Notice how, in the function definition, we only needed to specify the type of the object contained in the tuple `urls`, and the type for the values of the `query_params` dictionary. Declaring `*urls: str` is equivalent to `tuple[str, …]`, while `**query_params: str` is equivalent to `dict[str, str]`.

Protocols

Let us conclude our journey through type annotations by discussing **protocols**. In object-oriented programming, protocols define a set of methods that a class must implement without enforcing inheritance from any specific class. They are akin to the concept of interfaces in other languages, but they are more flexible and informal. They promote the use of polymorphism by allowing different classes to be used interchangeably if they follow the same protocol, even if they don't share a common base class.

This concept has been part of Python since the beginning. This type of protocol is normally referred to as a **dynamic protocol**, and it is described in the Data Model chapter (`https://docs.python.org/3/reference/datamodel.html`) of the **Python Language Reference**.

In the context of type hints, however, a protocol is a subclass of `typing.Protocol`, which defines an interface that a type checker can verify.

Introduced by PEP 544 (`https://peps.python.org/pep-0544/`), they enable structural subtyping (informally known as *static duck typing*), which we explored briefly at the beginning of this chapter.

The compatibility of an object with a protocol is determined by the presence of certain methods or attributes, rather than inheritance from a specific class.

Protocols are therefore quite helpful in those cases where we cannot easily define a type, and instead, it is more convenient to express the annotation in the form of *"it should support certain methods or have certain attributes."*

Protocols defined by PEP 544 are commonly referred to as **static protocols**.

Dynamic and static protocols present two key differences:

- Dynamic protocols allow for partial implementation. This means an object can provide an implementation for only a subset of the methods of the protocol and still be useful. However, static protocols require an object to provide *every* method declared in the protocol, even if the software doesn't need them all.
- Static protocols can be verified by static type checkers, while dynamic ones cannot.

You can find a list of the protocols provided by the `typing` module here: `https://docs.python.org/3/library/typing.html#protocols`. Their names are prefixed with the word `Supports`, followed by a title-cased version of the dunder method they declare to support. Some examples are:

- `SupportsAbs`: An ABC with one abstract method, `__abs__`.
- `SupportsBytes`: An ABC with one abstract method, `__bytes__`.
- `SupportsComplex`: An ABC with one abstract method, `__complex__`.

Other protocols that used to live in the `typing` module but have been migrated to `collections.abc` are `Iterable`, `Iterator`, `Sized`, `Container`, `Collection`, `Reversible`, and `ContextManager`, to name just a few.

You can find the complete list in the Mypy documentation: `https://mypy.readthedocs.io/en/stable/protocols.html#predefined-protocols-reference`.

Now that we have an idea about what a protocol is, in the context of type hints, let us see an example that shows how to create a simple custom protocol:

```
# annotations/protocols.py
from typing import Iterable, Protocol

class SupportsStart(Protocol):
    def start(self) -> None: ...

class Worker:  # No SupportsStart base class.
    def __init__(self, name: str) -> None:
        self.name = name

    def start(self) -> None:
        print(f"Starting worker {self.name}")

def start_workers(workers: Iterable[SupportsStart]) -> None:
    for worker in workers:
        worker.start()

workers = [Worker("Alice"), Worker("Bob")]
start_workers(workers)
```

In the code above, we define a protocol class, `SupportsStart`, which has one method: `start()`. To make it a static protocol, `SupportsStart` inherits from `Protocol`. The interesting part comes right after it, when we create the `Worker` class. Note that there is no need for it to inherit from the `SupportsStart` class. The `Worker` class only needs to fulfill the protocol, which means it needs to have a `start()` method.

We also wrote a function, `start_workers()`, which takes a parameter, `workers`, annotated as `Iterable[SupportsStart]`. That is all that is required to use a protocol. We define a couple of workers, `Alice` and `Bob`, and we pass them to the function call.

Running the above example will produce the following output:

```
Starting worker Alice
Starting worker Bob
```

Now imagine we also wanted to stop a worker. This is a more interesting case because it allows us to discuss how to subclass protocols. Let us see an example:

```
# annotations/protocols.subclassing.py
from typing import Iterable, Protocol

class SupportsStart(Protocol):
    def start(self) -> None: ...

class SupportsStop(Protocol):
    def stop(self) -> None: ...

class SupportsWorkCycle(SupportsStart, SupportsStop, Protocol):
    pass

class Worker:
    def __init__(self, name: str) -> None:
        self.name = name

    def start(self) -> None:
        print(f"Starting worker {self.name}")

    def stop(self) -> None:
        print(f"Stopping worker {self.name}")
```

```
def start_workers(workers: Iterable[SupportsWorkCycle]) -> None:
    for worker in workers:
        worker.start()
        worker.stop()

workers = [Worker("Alice"), Worker("Bob")]
start_workers(workers)
```

In the above example, we learned that we can compose protocols as we would do mixins. The one key difference is that when we subclass a protocol class, as in the case of `SupportsWorkCycle`, we still need to explicitly add `Protocol` to the list of base classes. If we do not do this, the static type checker will complain. This is because inheriting from an existing protocol does not automatically turn the subclass into a protocol. It only creates a regular class or ABC that implements the given protocol(s).

You can find more information about protocols in the Mypy documentation: `https://mypy.readthedocs.io/en/stable/protocols.html`.

Let us now discuss Mypy, the static type checker most widely adopted by the Python community.

The Mypy static type checker

There are several static type checkers for Python. Currently, the most widely adopted are:

- **Mypy**: Designed to work seamlessly with Python's type annotations defined by PEP 484, it supports gradual typing, integrates well with existing codebases, and has extensive documentation. You can find it at `https://mypy.readthedocs.io/`.
- **Pyright**: Developed by Microsoft, this fast type checker is optimized for use with Visual Studio Code. It does incremental analysis for fast type checking and supports both TypeScript and Python. You can find it at `https://github.com/microsoft/pyright`.
- **Pylint**: A comprehensive static analysis tool that includes type checking along with linting and code quality checks. It's highly configurable, supports custom plugins, and generates detailed code quality reports. You can find it at `https://pylint.org/`.
- **Pyre**: Developed by Facebook, it's fast and scalable, and works well with large codebases. It supports gradual typing, and has a powerful type inference engine. It also integrates well with continuous integration systems. You can find it at `https://pyre-check.org/`.

- **Pytype**: Developed by Google, it infers types automatically and reduces the need for explicit annotations, which it can generate. It integrates well with Google open-source tools. You can find it at `https://github.com/google/pytype`.

For this section of the chapter, we have decided to go with Mypy, since it currently seems to be the most popular.

To install it in your virtual environment, you can run the following command:

```
$ pip install mypy
```

Mypy is also included in the requirements file for this chapter. When Mypy is installed, you can run it against any files or folders you want. Mypy will recursively traverse any folder to find Python modules (`*.py` files). Here is an example:

```
$ mypy program.py some_folder another_folder
```

The command sports a massive set of options, which we encourage you to explore by running:

```
$ mypy --help
```

Let us start with a very simple example of a function that has no annotations and see the outcome of running `mypy` against it.

```
# mypy_src/simple_function.py
def hypothenuse(a, b):
    return (a**2 + b**2) ** 0.5
```

Running `mypy` on this module gives this result:

```
$ mypy simple_function.py
Success: no issues found in 1 source file
```

This is probably not what you expected, but Mypy is designed to support gradually adding type annotations to existing codebases. Outputting error messages for unannotated code would discourage developers from using it in this way. Therefore, the default behavior is to ignore functions that have no annotations. If we wanted Mypy to check the `hypothenuse()` function anyway, we could run it like this (notice we have re-formatted the output to fit the book's width):

```
$ mypy --strict mypy_src/simple_function.py
mypy_src/simple_function.py:4:
    error: Function is missing a type annotation  [no-untyped-def]
Found 1 error in 1 file (checked 1 source file)
```

Now Mypy is telling us that the function is missing a type annotation, so let us fix that.

```
# mypy_src/simple_function_annotated.py
def hypothenuse(a: float, b: float) -> float:
    return (a**2 + b**2) ** 0.5
```

We can run `mypy` again:

```
$ mypy simple_function_annotated.py
Success: no issues found in 1 source file
```

Excellent – now the function is annotated, and `mypy` runs successfully. Let us try out some function calls:

```
print(hypothenuse(3, 4))  # This is fine
print(hypothenuse(3.5, 4.9))  # This is also fine
print(hypothenuse(complex(1, 2), 10))  # Type checker error
```

The first two calls are fine, but the last one generates an error:

```
$ mypy mypy_src/simple_function_annotated.py
mypy_src/simple_function_annotated.py:10:
    error: Argument 1 to "hypothenuse" has incompatible
    type "complex"; expected "float"  [arg-type]
Found 1 error in 1 file (checked 1 source file)
```

Mypy is informing us that passing a `complex` where a `float` is required is not okay. The two types are not compatible.

Let us try a slightly more complex example (no pun intended):

```
# mypy_src/case.py
from collections.abc import Iterable

def title(names: Iterable[str]) -> list[str]:
    return [name.title() for name in names]

print(title(["ALICE", "bob"]))  # ['Alice', 'Bob'] - mypy OK
print(title([b"ALICE", b"bob"]))  # [b'Alice', b'Bob'] - mypy ERR
```

The above function applies title-casing to each string in `names`. First, we call it once, with the strings `"ALICE"` and `"bob"`, and then we call it with the `bytes` objects `b"ALICE"` and `b"bob"`. Both calls succeed because both the `str` and `bytes` objects have `title()` methods. However, running `mypy` yields the following result:

```
$ mypy mypy_src/case.py
mypy_src/case.py:10:
    error: List item 0 has incompatible type "bytes";
    expected "str"  [list-item]
mypy_src/case.py:10:
    error: List item 1 has incompatible type "bytes";
    expected "str"  [list-item]
Found 2 errors in 1 file (checked 1 source file)
```

Once again, Mypy is pointing out the incompatibility of two types – this time, `str` and `bytes`. We can easily fix this, by either amending the second call or changing the type annotation on the function. Let us do the latter:

```
# mypy_src/case.fixed.py
from collections.abc import Iterable

def title(names: Iterable[str | bytes]) -> list[str | bytes]:
    return [name.title() for name in names]

print(title(["ALICE", "bob"]))  # ['Alice', 'Bob'] - mypy OK
print(title([b"ALICE", b"bob"]))  # [b'Alice', b'Bob'] - mypy OK
```

Now, we use the union of the `str` and `bytes` types in the annotation, and `mypy` runs successfully.

Our advice is to install Mypy and run it against any existing codebase you might have. Try to introduce type annotations gradually and use Mypy to check the correctness of your code. This exercise will help you to acquire familiarity with type hints, and it will also benefit your code.

Some useful resources

We would recommend reading through (or at least skimming) all the PEPs we listed at the beginning of the chapter. We also recommend studying the various resources we pointed out along the way, some of which are listed below for your convenience:

- Python Typing Documentation:

`https://typing.readthedocs.io/en/latest/`

- Static Typing with Python:

  `https://docs.python.org/3/library/typing.html`

- Abstract Base Classes:

  `https://docs.python.org/3/library/abc.html`

- Abstract Base Classes for Containers:

  `https://docs.python.org/3/library/collections.abc.html`

- The Mypy Documentation:

  `https://mypy.readthedocs.io/en/stable/`

There is also a quick *Python Types Intro* section in the FastAPI framework documentation, which we would recommend reading: `https://fastapi.tiangolo.com/python-types/`.

FastAPI is a modern Python framework for building APIs. *Chapter 14*, *Introduction to API Development*, is dedicated to it, so we recommend at least reading the introduction on types prior to reading that chapter.

Summary

In this chapter, we have explored the topic of type hints in Python. We started by understanding Python's native approach to types and walked through the history of type hints, which were introduced gradually from Python 3 and are still evolving.

We investigated the benefits of type hints and then learned how to annotate functions, classes, and variables. We explored the basics and discussed the main built-in types, but also ventured through more advanced topics, such as generics, abstract base classes, and protocols.

Finally, we offered a few examples of how to use the most popular static type checker, Mypy, to gradually introduce typing in a codebase and finished the chapter with a short recap of the most useful resources for you to further investigate this subject.

This brings us to the end of the theory part of the book. The remaining chapters are project-oriented and take a more practical approach, starting with an introduction to data science. The knowledge acquired by studying the chapters in the first part should be sufficient to support you while you make your way through the next chapters.

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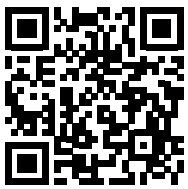
`https://discord.com/invite/uaKmaz7FEC`



13

Data Science in Brief

> *"If we have data, let's look at data. If all we have are opinions, let's go with mine."*
>
> *— Jim Barksdale, former Netscape CEO*

Data science is a broad term that can have different meanings depending on the context, understanding, and tools, amongst other factors. To do proper data science, you need to, at the very least, know mathematics and statistics. Then, you may want to dig into other subjects, such as pattern recognition and machine learning, and, of course, there is a plethora of languages and tools you can use.

We will not be able to talk about everything here. Therefore, to render this chapter meaningful, we are going to work on a project together instead.

Around 2012/2013, Fabrizio was working for a top-tier social media company in London. He stayed there for two years and was privileged to work with several very brilliant people. The company was the first in the world to have access to the Twitter Ads API, and they were partners with Facebook as well. That means a lot of data.

Their analysts were dealing with a vast number of campaigns, and they were struggling with the amount of work they had to do, so the development team Fabrizio was a part of tried to help by introducing them to Python and to the tools Python gives us to deal with data. It was an interesting journey that led him to mentor several people in the company, eventually taking him to Manila, where he gave a two-week intensive training course in Python and data science to the analysts over there.

The project we are going to do in this chapter is a lightweight version of the final example Fabrizio presented to his students in Manila. We have rewritten it to a size that will fit this chapter and made a few adjustments here and there for teaching purposes, but all the main concepts are there, so it should be fun and instructional for you.

Specifically, we are going to explore the following:

- The Jupyter Notebook and JupyterLab
- pandas and NumPy: the main libraries for data science in Python
- A few concepts around pandas's `DataFrame` class
- Creating and manipulating a dataset

Let us start by talking about Roman gods.

IPython and Jupyter Notebook

In 2001, Fernando Perez was a graduate student in physics at CU Boulder and was trying to improve the Python shell so that he could have the niceties he was used to when working with tools such as Mathematica and Maple. The result of these efforts took the name **IPython**.

That small script began as an enhanced version of the Python shell and, through the efforts of other coders and eventually with funding from several different companies, it became the successful project it is today. Some 10 years after its birth, a Notebook environment was created, powered by technologies such as WebSockets, the Tornado web server, jQuery, CodeMirror, and MathJax. The ZeroMQ library was also used to handle the messages between the Notebook interface and the Python core that lies behind it.

The IPython Notebook became so popular and widely used that, over time, numerous features were added to it. It can handle widgets, parallel computing, various media formats, and much more. Moreover, at some point, it became possible to code in languages other than Python from within the Notebook.

Eventually, the project was split into two: IPython has been stripped down to focus more on the kernel and the shell, while the Notebook has become a new project called **Jupyter**. Jupyter allows interactive scientific computations to be done in more than 40 languages. More recently, the Jupyter project has created **JupyterLab**, a web-based **IDE** incorporating Jupyter notebooks, interactive consoles, a code editor, and more.

This chapter's project will all be coded and run in a Jupyter Notebook, so let us briefly explain what a Notebook is. A Notebook environment is a web page that exposes a simple menu and cells in which you can run Python code. Even though the cells are separate entities that you can run individually, they all share the same Python kernel. This means that all the names that you define in one cell (the variables, functions, and so on) will be available in any other cell.

Simply put, a Python kernel is a process in which Python is running. The Notebook web page is an interface exposed to the user for driving this kernel. The web page communicates with it using a fast messaging system.

Apart from all the graphical advantages, the beauty of having such an environment lies in the ability to run a Python script in chunks, and this can be a tremendous advantage. Take a script that connects to a database to fetch data and then manipulates that data. If you do it in the conventional way, with a Python script, you have to fetch the data every time you want to experiment with it. Within a Notebook environment, you can fetch the data in one cell and then manipulate and experiment with it in other cells, so fetching it every time is not necessary.

The Notebook environment is also helpful for data science because it allows for the step-by-step inspection of results. You do one chunk of work and then verify it. You then do another chunk and verify again, and so on.

It is also invaluable for prototyping because the results are there, right in front of your eyes, immediately available.

If you would like to know more about these tools, please check out `ipython.org` and `jupyter.org`.

We have created a simple example Notebook with a `fibonacci()` function that gives you a list of all the Fibonacci numbers smaller than a given `N`. It looks like this:

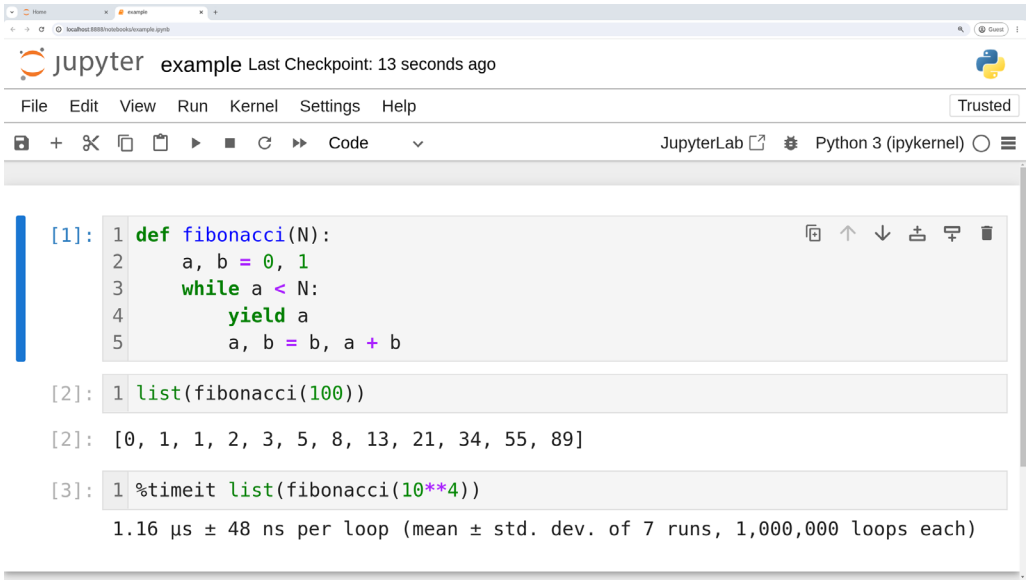


Figure 13.1: A Jupyter Notebook

Every cell has a label in square brackets, like **[1]**. If there is nothing between the brackets, it means that the cell has never been executed. If there is a number, it means that the cell has been executed, and the number represents the order in which the cell was executed. An asterisk, like *****, means that the cell is currently being executed.

You can see in the screenshot that in the first cell we have defined the `fibonacci()` function and executed it. This has the effect of placing the `fibonacci` name in the global scope associated with the Notebook, and therefore the `fibonacci()` function is now available to the other cells as well. In fact, in the second cell, we can run `list(fibonacci(100))` and see the results output below cell **[2]** (the output for each cell is labeled with the same number as the cell itself). In the third cell, we have shown you one of the several "magic" functions you can find in a Notebook: `%timeit` runs the code several times and provides you with a benchmark for it (this is implemented using the `timeit` module, which we briefly introduced in *Chapter 11, Debugging and Profiling*).

You can execute a cell as many times as you want and change the order in which you run them. Cells are very versatile: you can also have Raw cells, which contain plain text, or Markdown cells, which are useful for adding formatted textual explanations or headings.

Markdown is a lightweight markup language with plain text formatting syntax designed so that it can be converted to HTML and many other formats.

Another useful feature is that whatever you place in the last line of a cell will automatically be printed for you. This means you are not forced to explicitly write `print(…)` every time you want to inspect a value.

Using Anaconda

As usual, you can install the libraries required for this chapter using the `requirements.txt` file in the source code for the chapter. Sometimes, however, installing data science libraries can be quite painful. If you are struggling to install the libraries for this chapter in your virtual environment, you could install Anaconda instead. Anaconda is a free and open-source distribution of the Python and R programming languages for data science and machine learning-related applications, which aims to simplify package management and deployment. You can download it from the `anaconda.org` website. Once you have installed it, you can use the Anaconda interface to create a virtual environment and install the packages listed in the `requirements.in` file, which you can also find in the source code for the chapter.

Starting a Notebook

Once you have all the required libraries installed, you can start a Notebook with the following command:

```
$ jupyter notebook
```

If you install the requirements via Anaconda, you can also launch the Notebook from the Anaconda interface. In either case, you will have an open page in your web browser at this address (the port might be different): `http://localhost:8888/`.

You can also launch JupyterLab from Anaconda, or with the following command:

```
$ jupyter lab
```

It will also open as a new page in your web browser.

Explore both interfaces. Create a new Notebook or open the `example.ipynb` Notebook we showed you above. See which interface you prefer and get comfortable with it before proceeding with the rest of the chapter. We have included a saved JupyterLab workspace containing the Notebooks used in the rest of this chapter in the source code for the chapter (the file is called `ch13.jupyterlab-workspace`). You can use that to follow along in JupyterLab or stick to the classic Notebook interface if you prefer.

Alternatively, if you use a modern IDE to follow the chapter's example, it's likely you will be able to install a plugin to work with a notebook directly from inside the IDE.

To help you follow along, we will tag each code example in this chapter with the Notebook cell number it belongs to.

If you familiarize yourself with the keyboard shortcuts (look in the classic Notebook **Help** menu or the **Settings Editor** in JupyterLab), you will be able to move between cells and handle their content without having to reach for the mouse. This will make you much faster when you work in a Notebook.

Let us now move on and talk about the most interesting part of this chapter: data.

Dealing with data

Typically, when you deal with data, this is the path you go through: you fetch it; you clean and manipulate it; and then you analyze it and present results as values, spreadsheets, graphs, and so on. We want you to be able to perform all three steps of the process without having any external dependency on a data provider, so we are going to do the following:

1. Create the data, simulating that it comes in a format that is not perfect or ready to be worked on.
2. Clean it and feed it to the main tool we will use in the project, which is a `DataFrame` from the `pandas` library.
3. Manipulate the data in a `DataFrame`.
4. Save a `DataFrame` to a file in different formats.
5. Analyze the data and get some results out of it.

Setting up the Notebook

First, let us produce the data. We start from the `ch13-dataprep` Notebook. Cell `#1` takes care of the imports:

```
#1
import json
import random
from datetime import date, timedelta

import faker
```

The only modules we have not already encountered are `random` and `faker`. `random` is a standard library module for generating pseudo-random numbers. `faker` is a third-party module for generating fake data. It is particularly useful in tests, when you prepare your fixtures, to get all sorts of things such as names, email addresses, phone numbers, and credit card details.

Preparing the data

We want to achieve the following data structure: we are going to have a list of user objects. Each user object will be linked to several campaign objects. In Python, everything is an object, so we are using this term in a generic way. The user object may be a string, a dictionary, or something else.

A **campaign** in the social media world is a promotional campaign that a media agency runs on social media networks on behalf of a client. Remember that we are going to prepare this data so that it is not in perfect shape. Firstly, we instantiate the `Faker` that we will use to create the data:

```
#2
fake = faker.Faker()
```

This will internally keep track of values that have been generated and only yield unique values. We use a list comprehension to generate 1,000 unique usernames.

Next, we create a list of `users`. We will generate 1,000 `user` dictionaries with details such as `username`, `name`, `gender`, and `email`. Each `user` dictionary is then dumped to JSON and added to the list. This data structure is not optimal, of course, but we are simulating a scenario where users come to us like that.

```
#3
def get_users(no_of_users):
    usernames = (
        fake.unique.user_name() for i in range(usernames_no)
    )
    genders = random.choices(
        ["M", "F", "O"], weights=[0.43, 0.47, 0.1], k=no_of_users
    )
    for username, gender in zip(usernames, genders):
        name = get_random_name(gender)
        user = {
            "username": username,
            "name": name,
            "gender": gender,
            "email": fake.email(),
            "age": fake.random_int(min=18, max=90),
            "address": fake.address(),
        }
        yield json.dumps(user)

def get_random_name(gender):
    match gender:
        case "F":
            name = fake.name_female()
```

```
            case "M":
                name = fake.name_male()
            case _:
                name = fake.name_nonbinary()
        return name

users = get_users(1000)
users[:3]
```

The `get_users()` generator function takes the number of users to create as a parameter. We use `fake.unique.user_name()` in a generator expression to generate unique usernames. The `fake.unique` property keeps track of values that have been generated and yields only unique values. Next, we call `random.choices()` to generate a list of `no_of_users` random elements from the list `["M", "F", "O"]` (to represent male, female, or other genders). The weights 0.43, 0.47, and 0.1 will ensure that roughly 43% of our users will be male, 47% female, and 10% will not identify as either male or female. We use `zip()` to iterate over the usernames and genders. For each user, we call `get_random_name()`, which uses a `match` statement to generate a gender-appropriate name, and then generate a fake email address, age, and address. We dump the user data in a JSON string and `yield` it.

Also note the last line in the cell. Each cell automatically prints what is on the last line; therefore, the output of #3 is a list with the first three users:

```
['{"username": "epennington", "name": "Stephanie Gonzalez", ...}',
'{"username": "joshua61", "name": "Diana Richards", ...}',
'{"username": "dmoore", "name": "Erin Rose", "gender": "F",...}']
```

We hope you are following along with your own Notebook. If you are, please note that all data is generated using random functions and values; therefore, you will see different results. They will change every time you execute the Notebook. Also note that we have had to trim most of the output in this chapter to fit onto the page, so you will see a lot more output in your Notebook than we have reproduced here.

Analysts use spreadsheets all the time, and they create all sorts of coding techniques to compress as much information as possible into the campaign names. The format we have chosen is a simple example of that technique—there is a code that tells us the campaign type, then the start and end dates, then the target age and `gender` (`"M"` for male, `"F"` for female, or `"A"` for any), and finally the currency.

All values are separated by an underscore. The code to generate these campaign names can be found in cell #4:

```
#4
# campaign name format:
# InternalType_StartDate_EndDate_TargetAge_TargetGender_Currency
def get_type():
    # just some meaningless example codes
    types = ["AKX", "BYU", "GRZ", "KTR"]
    return random.choice(types)

def get_start_end_dates():
    duration = random.randint(1, 2 * 365)
    offset = random.randint(-365, 365)
    start = date.today() - timedelta(days=offset)
    end = start + timedelta(days=duration)

    def _format_date(date_):
        return date_.strftime("%Y%m%d")
    return _format_date(start), _format_date(end)

def get_age_range():
    age = random.randrange(20, 46, 5)
    diff = random.randrange(5, 26, 5)
    return "{}-{}".format(age, age + diff)

def get_gender():
    return random.choice(("M", "F", "A"))

def get_currency():
    return random.choice(("GBP", "EUR", "USD"))

def get_campaign_name():
    separator = "_"
    type_ = get_type()
    start, end = get_start_end_dates()
    age_range = get_age_range()
    gender = get_gender()
```

```
    currency = get_currency()
    return separator.join(
        (type_, start, end, age_range, gender, currency)
    )
```

In the `get_type()` function, we use `random.choice()` to get one value randomly out of a collection. `get_start_end_dates()` is a bit more interesting. We compute two random integers: the `duration` of the campaign in days (between one day and two years) and an `offset` (a number of days between –365 and 365). We subtract `offset` (as a `timedelta`) from today's date to get the start date and add the `duration` to get the end date. Finally, we return string representations of both dates.

The `get_age_range()` function generates a random target age range, where both endpoints are multiples of five. We use the `random.randrange()` function, which returns a random number from a range defined by `start`, `stop`, and `step` parameters (these parameters have the same meaning as for the `range` object that we first encountered in *Chapter 3, Conditionals and Iteration*). We generate random numbers `age` (a multiple of 5 between 20 and 46) and `diff` (a multiple of 5 between 5 and 26). We add `diff` to `age` to get the upper limit of our age range and return a string representation of the age range.

The rest of the functions are just some applications of `random.choice()` and the last one, `get_campaign_name()`, assembles all the pieces and returns the final campaign name.

In `#5`, we write a function that creates a complete campaign object:

```
#5
# campaign data:
# name, budget, spent, clicks, impressions
def get_campaign_data():
    name = get_campaign_name()
    budget = random.randint(10**3, 10**6)
    spent = random.randint(10**2, budget)
    clicks = int(random.triangular(10**2, 10**5, 0.2 * 10**5))
    impressions = int(random.gauss(0.5 * 10**6, 2))
    return {
        "cmp_name": name,
        "cmp_bgt": budget,
        "cmp_spent": spent,
        "cmp_clicks": clicks,
```

```
        "cmp_impr": impressions,
    }
```

We used a few functions from the `random` module. `random.randint()` gives you an integer between two extremes. It follows a uniform probability distribution, which means that any number in the interval has the same probability of coming up. To avoid having all our data look similar, we chose to use `triangular()` and `gauss()`, for `clicks` and `impressions`. They use different probability distributions so that we will have something more interesting to see in the end.

Just to make sure we are on the same page with the terminology: `clicks` represents the number of clicks on a campaign advertisement, `budget` is the total amount of money allocated for the campaign, `spent` is how much of that money has already been spent, and `impressions` is the number of times the campaign has been displayed, regardless of the number of clicks that were performed on the campaign. Normally, the number of `impressions` is greater than the number of `clicks` because an advertisement is often viewed without being clicked on.

Now that we have the data, we can put it all together:

```
#6
def get_data(users):
    data = []
    for user in users:
        campaigns = [
            get_campaign_data()
            for _ in range(random.randint(2, 8))
        ]
        data.append({"user": user, "campaigns": campaigns})
    return data
```

As you can see, each item in `data` is a dictionary with a `user` and a list of campaigns that are associated with that `user`.

Cleaning the data

Next, we can start cleaning the data:

```
#7
rough_data = get_data(users)
rough_data[:2]  # let us take a peek
```

We simulate fetching the data from a source and then inspect it. The Notebook is the perfect tool for inspecting your steps.

You can vary the granularity to suit your needs. The first item in `rough_data` looks like this:

```
 {'user': '{"username": "epennington", "name": ...}',
  'campaigns': [{'cmp_name': 'KTR_20250404_20250916_35-50_A_EUR',
    'cmp_bgt': 964496,
    'cmp_spent': 29586,
    'cmp_clicks': 36632,
    'cmp_impr': 500001},
   {'cmp_name': 'AKX_20240130_20241017_20-25_M_GBP',
    'cmp_bgt': 344739,
    'cmp_spent': 166010,
    'cmp_clicks': 67325,
    'cmp_impr': 499999}]}
```

Now we can start working on the data. The first thing we need to do to be able to work with this `data` is to denormalize it. **Denormalization** is a process of restructuring data into a single table. This involves merging data from multiple tables or flattening out nested data structures. It usually introduces some duplication of data; however, it simplifies data analysis by eliminating the need to deal with nested structures or to look related data up across multiple tables. In our case, this means transforming `data` into a list whose items are campaign dictionaries, augmented with their relative `user` dictionary. Users will be duplicated in each campaign they are associated with:

```
#8
data = []
for datum in rough_data:
    for campaign in datum["campaigns"]:
        campaign.update({"user": datum["user"]})
        data.append(campaign)
data[:2]  # Let us take another peek
```

The first item in `data` now looks like this:

```
 {'cmp_name': 'KTR_20250404_20250916_35-50_A_EUR',
  'cmp_bgt': 964496,
  'cmp_spent': 29586,
```

```
 'cmp_clicks': 36632,
 'cmp_impr': 500001,
 'user': '{"username": "epennington", ...}'},
```

Now, we would like to help you and offer a deterministic second part of the chapter, so we are going to save the data we generated here so that we (and you, too) will be able to load it from the next Notebook, and we should then have the same results:

```
#9
with open("data.json", "w") as stream:
    stream.write(json.dumps(data))
```

You should find the `data.json` file in the source code for the book. Now, we are done with `ch13-dataprep`, so we can close it and open the `ch13` notebook.

Creating the DataFrame

Now that we have prepared our data, we can start analyzing it. First, we have another round of imports:

```
#1
import json

import arrow
import pandas as pd
from pandas import DataFrame
```

We have already seen the `json` module in *Chapter 8, Files and Data Persistence*. We also briefly introduced `arrow` in *Chapter 2, Built-In Data Types*. It is a very useful third-party library that makes working with dates and times a lot easier. `pandas` is the core upon which the whole project is based. **pandas** stands for **Python Data Analysis Library**. Among many other things, it provides the `DataFrame`, a matrix-like data structure with advanced processing capabilities. It is customary to `import pandas as pd` and also import `DataFrame` separately.

After the imports, we load our data into a `DataFrame` using the `pandas.read_json()` function:

```
#2
df = pd.read_json("data.json")
df.head()
```

We inspect the first five rows using the `head()` method of `DataFrame`. You should see something like this:

	cmp_name	cmp_bgt	cmp_spent	cmp_clicks	cmp_impr	user
0	KTR_20250404_20250916_35-50_A_EUR	964496	29586	36632	500001	{"username": "epennington", "name": "Stephanie...
1	AKX_20240130_20241017_20-25_M_GBP	344739	166010	67325	499999	{"username": "epennington", "name": "Stephanie...
2	BYU_20230828_20250115_25-45_M_GBP	177403	125738	29989	499997	{"username": "joshua61", "name": "Diana Richar...
3	AKX_20250216_20261129_45-60_F_USD	618256	75017	76301	500000	{"username": "joshua61", "name": "Diana Richar...
4	AKX_20231229_20250721_20-40_F_GBP	113805	12583	48915	500001	{"username": "joshua61", "name": "Diana Richar...

Figure 13.2: The first few rows of the DataFrame

Jupyter automatically renders the output of the `df.head()` call as HTML. To get a plain text representation, you can wrap `df.head()` in a `print` call.

The `DataFrame` structure allows you to perform various operations on its contents. You can filter by rows or columns, aggregate data, and so on. You can operate on entire rows or columns without suffering the time penalty you would have to pay if you were working on data with pure Python. This is possible because, under the hood, `pandas` harnesses the power of the **NumPy** library, which itself draws its incredible speed from the low-level implementation of its core.

NumPy stands for Numeric Python. It is one of the most widely used libraries in the data science environment.

Using `DataFrame` allows us to couple the power of NumPy with spreadsheet-like capabilities so that we can work on our data in a way that is similar to what an analyst would normally do, only we do it with code.

Let us see two ways to quickly get an overview of the data:

```
#3
df.count()
```

The `count()` method returns a count of all the non-empty cells in each column. This is useful to help you understand how sparse your data is. In our case, we have no missing values, so the output is:

`cmp_name`	5065
`cmp_bgt`	5065
`cmp_spent`	5065
`cmp_clicks`	5065
`cmp_impr`	5065
`user`	5065
`dtype: int64`	

We have 5,065 rows. Given that we have 1,000 users and the number of campaigns per user is a random number between 2 and 8, that is in line with what we would expect.

The `dtype: int64` line at the end of the output indicates that the values returned by `df.count()` are NumPy `int64` objects. Here, `dtype` stands for "data type" and `int64` means 64-bit integers. NumPy is largely implemented in C and, instead of using Python's built-in numeric types, it uses its own types, which are closely related to C language data types. This allows it to perform numerical operations much more quickly than pure Python.

The `describe` method is useful to quickly obtain a statistical summary of our data:

```
#4
df.describe()
```

As shown in the output below, it gives us several measures, such as `count`, `mean`, `std` (standard deviation), `min`, and `max`, and shows how data is distributed in the various quartiles. Thanks to this method, we already have an idea of how our data is structured:

	cmp_bgt	**cmp_spent**	**cmp_clicks**	**cmp_impr**
count	5065.000000	5065.000000	5065.000000	5065.000000
mean	502965.054097	253389.854689	40265.781639	499999.474630
std	290468.998656	222774.897138	21840.783154	2.023801
min	1764.000000	107.000000	899.000000	499992.000000
25%	251171.000000	67071.000000	22575.000000	499998.000000
50%	500694.000000	187743.000000	36746.000000	499999.000000
75%	756850.000000	391790.000000	55817.000000	500001.000000
max	999565.000000	984705.000000	98379.000000	500007.000000

We can use the `sort_values()` and `head()` methods to see the campaigns with the highest budgets:

```
#5
df.sort_values(by=["cmp_bgt"], ascending=False).head(3)
```

This gives the following output (we have omitted some columns to fit the output on the page):

	cmp_name	cmp_bgt	cmp_clicks	cmp_impr
3186	GRZ_20230914_20230929_40-60_A_EUR	999565	63869	499998
3168	KTR_20250315_20260507_25-40_M_USD	999487	21097	500000
3624	GRZ_20250227_20250617_30-45_F_USD	999482	3435	499998

Calling `tail()` instead of `head()` shows us the campaigns with the lowest budgets:

```
#6
df.sort_values(by=["cmp_bgt"], ascending=False).tail(3)
```

Next, we will take on some more complex tasks.

Unpacking the campaign name

Firstly, we want to get rid of the campaign name column (`cmp_name`). We need to explode it into parts and put each part in its own dedicated column. We will use the `apply()` method of the `Series` object to do this.

The `pandas.core.series.Series` class is a powerful wrapper around an array (think of it as a list with augmented capabilities). We can extract a `Series` object from `DataFrame` by accessing it in the same way we do with a key in a dictionary. We will then use the `apply()` method of the `Series` object to call a function on each item in the `Series` and obtain a new `Series` with the results. Finally, we compose the result into a new `DataFrame`, and then join that `DataFrame` with `df`.

We start by defining a function to split a campaign name into a tuple containing the type, start and end dates, target age, target gender, and currency. Note that we use `arrow.get()` to convert the start and end date strings to `date` objects.

```
#7
def unpack_campaign_name(name):
    # very optimistic method, assumes data in campaign name
    # is always in good state
    type_, start, end, age, gender, currency = name.split("_")
    start = arrow.get(start, "YYYYMMDD").date()
```

```
    end = arrow.get(end, "YYYYMMDD").date()
    return type_, start, end, age, gender, currency
```

Next, we extract the `Series` with the campaign names from `df` and apply the `unpack_campaign_name()` function to each name.

```
#8
campaign_data = df["cmp_name"].apply(unpack_campaign_name)
```

Now we can construct a new `DataFrame` from the `campaign_data`:

```
#9
campaign_cols = [
    "Type",
    "Start",
    "End",
    "Target Age",
    "Target Gender",
    "Currency",
]
campaign_df = DataFrame.from_records(
    campaign_data, columns=campaign_cols, index=df.index
)
campaign_df.head(3)
```

A quick peek at the first three rows reveals:

	Type	Start	End	Target Age	Target Gender	Currency
0	KTR	2025-04-04	2025-09-16	35-50	A	EUR
1	AKX	2024-01-30	2024-10-17	20-25	M	GBP
2	BYU	2023-08-28	2025-01-15	25-45	M	GBP

That looks better. Now, we can more easily work with the data represented by the column names. One important thing to remember: even if the dates are printed as strings, they are just the representation of the real `date` objects that are stored in `DataFrame`.

Finally, we can join the original `DataFrame` (`df`) and `campaign_df` into a single `DataFrame`. When joining two `DataFrame` instances, it is imperative that they have the same `index`, otherwise `pandas` will not be able to match up the rows. We took care of this by explicitly using the index from `df` when creating `campaign_df`.

```
#10
df = df.join(campaign_df)
```

Let us inspect the data to verify that everything matches correctly:

```
#11
df[["cmp_name"] + campaign_cols].head(3)
```

The first few columns of the output are as follows:

	cmp_name	Type	Start	End
0	KTR_20250404_20250916_35-50_A_EUR	KTR	2025-04-04	2025-09-16
1	AKX_20240130_20241017_20-25_M_GBP	AKX	2024-01-30	2024-10-17
2	BYU_20230828_20250115_25-45_M_GBP	BYU	2023-08-28	2025-01-15

As you can see, `join()` was successful; the campaign name and the separated columns represent the same data.

Note how we access the `DataFrame` using the square brackets syntax, passing a list of column names. This will produce a new `DataFrame`, with those columns (in the same order), on which we then call the `head()` method.

Unpacking the user data

We now do the same thing for each piece of `user` JSON data. We call `apply()` on the `user` series, running the `unpack_user_json()` function, which takes a JSON `user` object and transforms it into a list of its fields. We create a new `DataFrame`, `user_df`, with this data:

```
#12
def unpack_user_json(user):
    # very optimistic as well, expects user objects
    # to have all attributes
    user = json.loads(user.strip())
    return [
        user["username"],
```

```
        user["email"],
        user["name"],
        user["gender"],
        user["age"],
        user["address"],
    ]

user_data = df["user"].apply(unpack_user_json)
user_cols = [
    "username",
    "email",
    "name",
    "gender",
    "age",
    "address",
]
user_df = DataFrame.from_records(
    user_data, columns=user_cols, index=df.index
)
```

Next, we join `user_df` back with `df` (like we did with `campaign_df`), and inspect the result:

```
#13
df = df.join(user_df)
df[["user"] + user_cols].head(2)
```

The output shows us that everything went well.

Renaming columns

If you evaluate `df.columns` in a cell, you will see that we still have ugly names for our columns. Let us change that:

```
#14
new_column_names = {
    "cmp_bgt": "Budget",
    "cmp_spent": "Spent",
    "cmp_clicks": "Clicks",
    "cmp_impr": "Impressions",
}
df.rename(columns=new_column_names, inplace=True)
```

The `rename()` method can be used to change the column (or row) labels. We have given it a dictionary mapping old column names to our preferred names. Any column that is not mentioned in the dictionary will remain unchanged.

Computing some metrics

Our next step will be to add some additional columns. For each campaign, we have the number of clicks and impressions, and we have the amounts spent. This allows us to introduce three measurement ratios: `CTR`, `CPC`, and `CPI`. They stand for *Click Through Rate*, *Cost Per Click*, and *Cost Per Impression*, respectively.

The last two are straightforward, but `CTR` is not. Suffice it to say that it is the ratio between clicks and impressions. It gives you a measure of how many clicks were performed on a campaign advertisement per impression—the higher this number, the more successful the advertisement is in attracting users to click on it. Let us write a function that calculates all three ratios and adds them to the `DataFrame`:

```
#15
def calculate_metrics(df):
    # Click Through Rate
    df["CTR"] = df["Clicks"] / df["Impressions"]
    # Cost Per Click
    df["CPC"] = df["Spent"] / df["Clicks"]
    # Cost Per Impression
    df["CPI"] = df["Spent"] / df["Impressions"]

calculate_metrics(df)
```

Notice that we are adding those three columns with one line of code each, but the `DataFrame` applies the operation automatically (the division, in this case) to each pair of cells from the appropriate columns. So, even though it looks like we are only doing three divisions, there are actually *5,140 * 3* divisions because they are performed for each row. `pandas` does a lot of work for us while hiding much of the complexity of it.

The `calculate_metrics()` function takes a `DataFrame` (`df`) and works directly on it. This mode of operation is called **in-place**. This is similar to how the `list.sort()` method sorts a list. You could also say that this function is not pure, which means it has side effects, as it modifies the mutable object it is passed as an argument.

We can take a look at the results by filtering on the relevant columns and calling `head()`:

```
#16
df[["Spent", "Clicks", "Impressions", "CTR", "CPC", "CPI"]].head(
    3
)
```

This shows us that the calculations were performed correctly on each row:

	Spent	Clicks	Impressions	CTR	CPC	CPI
0	29586	36632	500001	0.073264	0.807655	0.059172
1	166010	67325	499999	0.134650	2.465800	0.332021
2	125738	29989	499997	0.059978	4.192804	0.251478

We can also verify the accuracy of the results manually for the first row:

```
#17
clicks = df["Clicks"][0]
impressions = df["Impressions"][0]
spent = df["Spent"][0]

CTR = df["CTR"][0]
CPC = df["CPC"][0]
CPI = df["CPI"][0]

print("CTR:", CTR, clicks / impressions)
print("CPC:", CPC, spent / clicks)
print("CPI:", CPI, spent / impressions)
```

This yields the following output:

```
CTR: 0.07326385347229306 0.07326385347229306
CPC: 0.8076545097182791 0.8076545097182791
CPI: 0.059171881656236686 0.059171881656236686
```

The values match, confirming that our computations are correct. Of course, we would not normally need to do this, but we wanted to show you how can you perform such calculations. You can access a `Series` (a column) by passing its name to the `DataFrame` in square brackets (this is similar to looking up a key in a dictionary). You can then access each row in the column by its position, exactly as you would with a regular list or tuple.

We are almost done with our `DataFrame`. All we are missing now is a column that tells us the duration of the campaign and a column that tells us which day of the week each campaign started on. The duration is important to have, since it allows us to relate data such as the amount spent or number of impressions to the duration of the campaign (we may expect longer-running campaigns to cost more and have more impressions). The day of the week can also be useful; for example, some campaigns may be tied to events that happen on particular days of the week (such as sports events that take place on weekends).

```
#18
def get_day_of_the_week(day):
    return day.strftime("%A")

def get_duration(row):
    return (row["End"] - row["Start"]).days

df["Day of Week"] = df["Start"].apply(get_day_of_the_week)
df["Duration"] = df.apply(get_duration, axis="columns")
```

`get_day_of_the_week()` takes a `date` object and formats it as a string that only contains the name of the corresponding day of the week. `get_duration()` is more interesting. First, notice that it takes an entire row, not just a single value. This function subtracts a campaign's start date from the end date. When you subtract `date` objects, the result is a `timedelta` object, which represents a given amount of time. We take the value of its `.days` property to get the duration in days.

We calculate the starting day of the week for each campaign by applying `get_day_of_the_week()` to the `Start` column (as a `Series` object); this is similar to what we did with `"user"` and `"cmp_name"`. Next, we apply `get_duration()` to the whole `DataFrame`. Note that we instruct `pandas` to operate on the rows by passing `axis="columns"`. This may seem counter-intuitive but think of it as passing all the columns to each call of `get_duration()`.

We can verify the results as shown in the next cell:

```
#19
df[["Start", "End", "Duration", "Day of Week"]].head(3)
```

This gives the following output:

	Start	End	Duration	Day of Week
0	2025-04-04	2025-09-16	165	Friday

1	2024-01-30	2024-10-17	261	Tuesday
2	2023-08-28	2025-01-15	506	Monday

So, we now know that there are 165 days between the 4th of April, 2025, and the 16th of September, 2025, and that the 15th of January, 2025, is a Monday.

Cleaning everything up

Now that we have everything we want, it is time to do the final cleaning; remember we still have the `"cmp_name"` and `"user"` columns. Those are no longer needed, so we will remove them. We also want to reorder the columns in our `DataFrame` so that they are more relevant to the data it now contains. We can accomplish this by filtering `df` on the column list we want. The result is a new `DataFrame` that we can reassign to the name `df`:

```
#19
final_columns = [
    "Type",
    "Start",
    "End",
    "Duration",
    "Day of Week",
    "Budget",
    "Currency",
    "Clicks",
    "Impressions",
    "Spent",
    "CTR",
    "CPC",
    "CPI",
    "Target Age",
    "Target Gender",
    "Username",
    "Email",
    "Name",
    "Gender",
    "Age",
]
df = df[final_columns]
```

We have grouped the campaign information at the beginning, then the measurements, and finally the user data at the end. Now our `DataFrame` is clean and ready for us to inspect.

Before we start creating some graphs, we want to take a snapshot of the `DataFrame` so that we can easily reconstruct it from a file without needing to redo all the steps we did to get here. Some analysts may want to have it in spreadsheet form, to do a different kind of analysis, so let us see how to save a `DataFrame` to a file.

Saving the DataFrame to a file

We can save a `DataFrame` in several formats. You can type `df.to_` and then press *Tab* to make autocompletion pop up, so you can see all the options.

We are going to save our `DataFrame` in three different formats. First, CSV:

```
#20
df.to_csv("df.csv")
```

Then JSON:

```
#21
df.to_json("df.json")
```

And finally, in an Excel spreadsheet:

```
#22
df.to_excel("df.xlsx")
```

The `to_excel()` method requires the `openpyxl` package to be installed. It is included in the `requirements.txt` file for this chapter, so if you used that to install the requirements, you should have it in your virtual environment.

As you can see, it is easy to save a `DataFrame` in many different formats. The good news is that the reverse is also true: it's equally easy to load a spreadsheet into a `DataFrame` (just use the `pandas` `read_csv()` or `read_excel()` functions).

Visualizing the results

In this section, we are going to visualize some results. From a data science perspective, we are not going to attempt an in-depth analysis of the data or try to draw any conclusions from it. It would not make much sense because the data is completely random. However, this example should still be enough to get you started with graphs and other features.

One lesson that we have learned the hard way is that appearance makes a difference in how people perceive your work. If you want to be taken seriously, think carefully about how you present your data and try to make your graphs and tables look appealing.

`pandas` uses the Matplotlib plotting library to draw graphs. We will not be using it directly, except to configure the plot style and save plots to disk. You can learn more about this versatile plotting library at `https://matplotlib.org/`.

First, we will configure the Notebook to render Matplotlib graphs as interactive widgets in the cell output frame. We do it with the following:

```
#23
%matplotlib widget
```

This will allow you to pan and zoom the figure and save a (low-resolution) snapshot to disk.

By default (without `%matplotlib widget`), figures will be rendered as static images in the cell output frame. Using the interactive widget mode requires the `ipympl` package to be installed. It is included in the `requirements.txt` file for this chapter, so if you used that to install the requirements, you should have it in your virtual environment.

Then, we set up some styling for our plots:

```
#24
import matplotlib.pyplot as plt
plt.style.use(["classic", "ggplot"])
plt.rc("font", family="serif"})
plt.rc("savefig", dpi=300)
```

We use the `matplotlib.pyplot` interface to set the plot style. We have chosen to use a combination of the `classic` and `ggplot` style sheets. Style sheets are applied from left to right, so here `ggplot` will override the `classic` style for any style items that are defined in both. We also set the font family used in the plots to `serif`. The `plt.rc("savefig", dpi=300)` call, configures the `savefig()` method to generate high-resolution image files that are suitable for printing.

Before we generate any graphs, let us run `df.describe()` (#26) again. The results should look like this:

	Duration	Budget	Clicks	Impressions	Spent	CTR	CPC	CPI	Age
count	5065.000000	5065.000000	5065.000000	5065.000000	5065.000000	5065.000000	5065.000000	5065.000000	5065.000000
mean	369.488253	502965.054097	40265.781639	499999.474630	253389.854689	0.080532	10.131895	0.506780	53.882330
std	209.852969	290468.998656	21840.783154	2.023801	222774.897138	0.043682	19.527218	0.445550	21.170077
min	1.000000	1764.000000	899.000000	499992.000000	107.000000	0.001798	0.001493	0.000214	18.000000
25%	192.000000	251171.000000	22575.000000	499998.000000	67071.000000	0.045150	1.756140	0.134143	35.000000
50%	371.000000	500694.000000	36746.000000	499999.000000	187743.000000	0.073493	5.207316	0.375486	54.000000
75%	554.000000	756850.000000	55817.000000	500001.000000	391790.000000	0.111634	11.630131	0.783572	72.000000
max	730.000000	999565.000000	98379.000000	500007.000000	984705.000000	0.196758	462.814233	1.969410	90.000000

Figure 13.3: Some statistics for our cleaned-up data

This kind of quick result is perfect for satisfying those managers who have 20 seconds to dedicate to you and just want rough numbers.

Once again, please keep in mind that our campaigns have different currencies, so these numbers are meaningless. The point here is to demonstrate the `DataFrame` capabilities, not to perform a correct or detailed analysis of real data.

Alternatively, a graph is usually much better than a table with numbers because it is much easier to read, and it gives you immediate feedback. So, let us plot the four pieces of information we have on each campaign: `"Budget"`, `"Spent"`, `"Clicks"`, and `"Impressions"`:

```
#27
df[["Budget", "Spent", "Clicks", "Impressions"]].hist(
    bins=16, figsize=(16, 6)
)
plt.savefig("Figure13.4.png")
```

We extract those four columns (this will give us another `DataFrame` made with only those columns) and call the `hist()` method to get a histogram plot. We give some arguments to specify the number of bins and figure sizes, and everything else is done automatically. The result looks as follows:

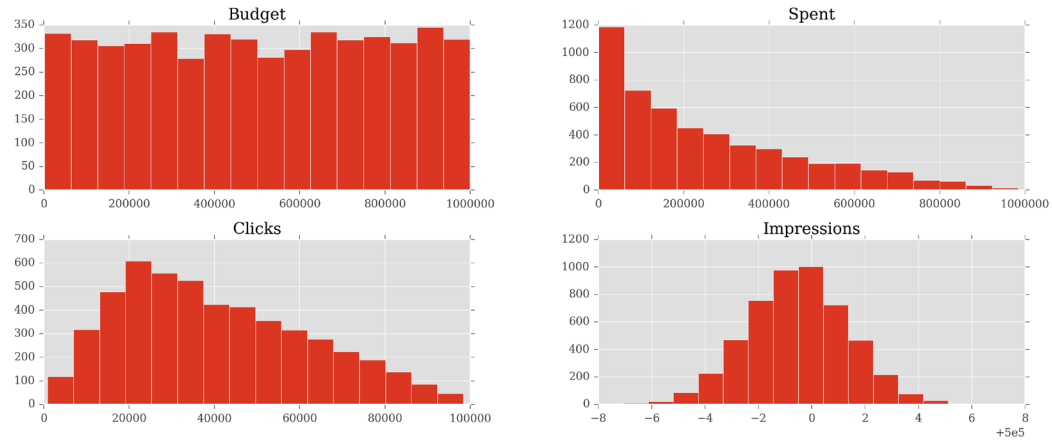


Figure 13.4: Histogram plots of the campaign data

We also call `plt.savefig("Figure13.4.png")` to save the image to a file named `Figure13.4.png`. This will use the `300dpi` setting we configured previously to generate a high-resolution image. Note that `plt.savefig()` will save the most recent image generated by Matplotlib. Calling it from the same cell where we generate the plot ensures that we save the correct image to the correct filename.

Although it is meaningless to try to interpret plots of random data, we can at least verify that what we see matches what we might expect, given how the data was generated.

- *Budget* is selected randomly from an interval, so we expect a uniform distribution. Looking at the graph, that is indeed what we see.
- *Spent* is also uniformly distributed, but its upper limit is the budget, which is not constant. This means we should expect a logarithmic curve that decreases from left to right. Again, that matches what the graph shows.
- *Clicks* was generated with a triangular distribution with a mean 20% of the interval size, and you can see that the peak is right there, at about 20% to the left.
- *Impressions* was a Gaussian distribution, which assumes the famous bell shape. The mean was exactly in the middle and we had a standard deviation of 2. You can see that the graph matches those parameters.

Let us also plot the metrics we calculated:

```
#28
df[["CTR", "CPC", "CPI"]].hist(bins=20, figsize=(16, 6))
plt.savefig("Figure13.5.png")
```

Here is the plot representation:

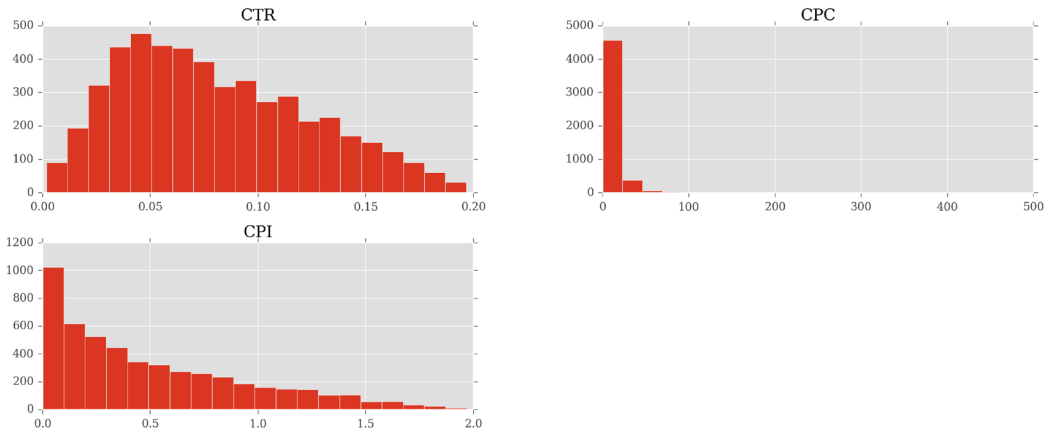


Figure 13.5: Histogram plots of computed measures

We can see that the *CPC* is highly skewed to the left, meaning that most of the *CPC* values are low. The *CPI* has a similar shape but is less extreme.

Now, suppose you want to analyze only a particular segment of the data. We can apply a mask to the `DataFrame` so that we get a new `DataFrame` with only the rows that satisfy the mask condition. It is like applying a global, row-wise `if` clause:

```
#29
selector = df.Spent > df.Budget * 0.75
df[selector][["Budget", "Spent", "Clicks", "Impressions"]].hist(
    bins=15, figsize=(16, 6), color="green"
)
plt.savefig("Figure13.6.png")
```

In this case, we prepared `selector` to filter out all the rows for which the amount spent is less than or equal to 75% of the budget. In other words, we will include only those campaigns for which we have spent at least three-quarters of the budget. Notice that in `selector`, we are showing you an alternative way of asking for a `DataFrame` column, by using direct property access (`object.property_name`), instead of dictionary-like access (`object['property_name']`). If `property_name` is a valid Python name, you can use both ways interchangeably.

`selector` is applied in the same way that we access a dictionary with a key. When we apply `selector` to `df`, we get a new `DataFrame`. We select only the relevant columns from this and call `hist()` again. This time, we set `color` to `green`, just to show how that can be done.

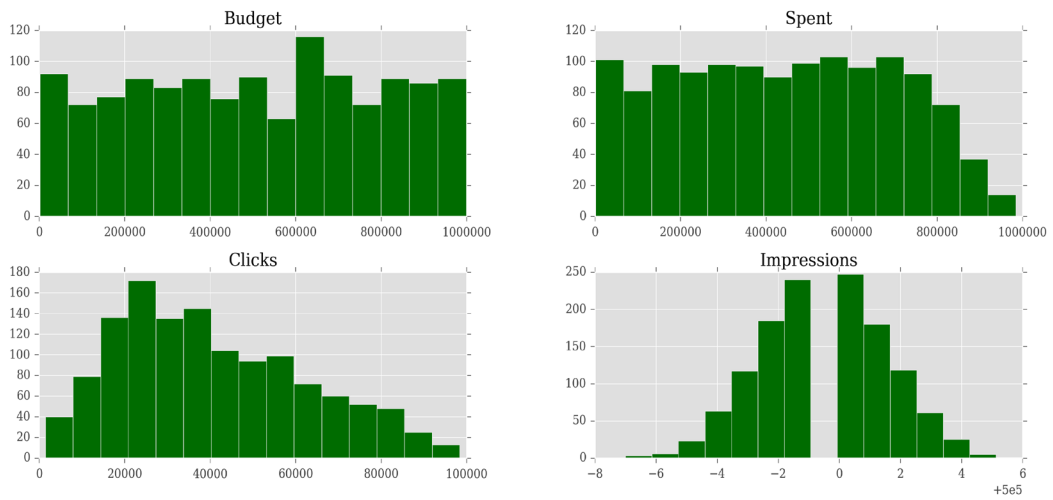


Figure 13.6: Histogram plots of campaign data where at least 75% of the budget was spent

Note that the shapes of the graphs have not changed much, apart from the *Spent* graph, which is quite different. This is because we have selected only the rows where the amount spent is at least 75% of the budget. This means that we are including only the rows where the amount spent is close to the budget. The budget numbers come from a uniform distribution. Therefore, the *Spent* graph is now assuming that kind of shape. If you make the boundary even tighter and ask for 85% or more, you will see the *Spent* graph become increasingly similar to *Budget*.

Let us also look at a different kind of plot. We will plot the sums of `"Spent"`, `"Clicks"`, and `"Impressions"` for each day of the week.

```
#30
df_weekday = df.groupby(["Day of Week"]).sum(numeric_only=True)
df_weekday[["Impressions", "Spent", "Clicks"]].plot(
    figsize=(16, 6), subplots=True
)
plt.savefig("Figure13.7.png")
```

The first line creates a new `DataFrame`, `df_weekday`, by asking for a grouping by `"Day of Week"` on `df`. We then aggregate, by computing the sum within each group. Note that we must pass `numeric_only=True` to avoid errors when attempting to sum columns with non-numeric data. We could also have taken a different approach by selecting only the columns we need (`"Day of Week"`, `"Impressions"`, `"Spent"`, and `"Clicks"`) before grouping and summing.

Note that this time we call `plot()` instead of `hist()`. This will draw a line graph instead of a histogram. The `subplots=True` option makes `plot` draw three separate graphs:

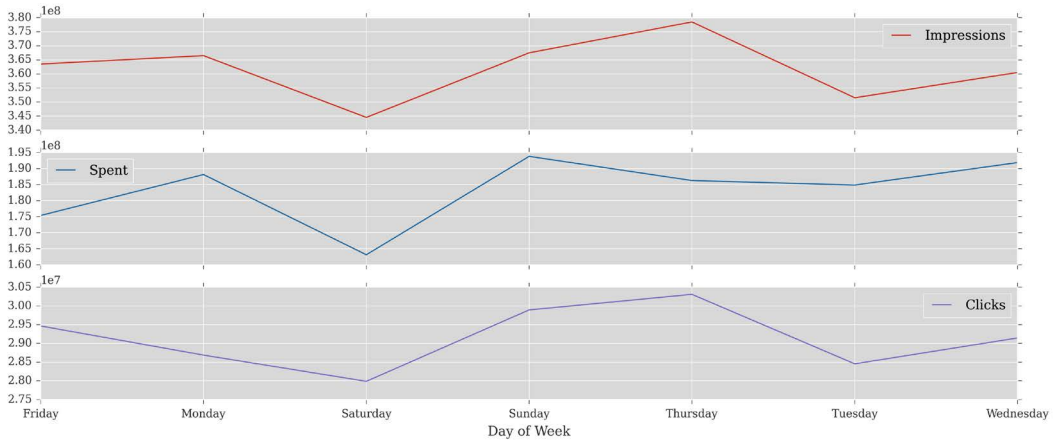


Figure 13.7: Plots of campaign data aggregated by day of the week

These plots show that campaigns that started on Thursdays got the most clicks and impressions, while campaigns that started on Saturdays spent the least money. If this were real data, this would potentially be important information to give to our clients.

Note that the days are sorted alphabetically, which makes the graph difficult to read. We will leave it to you as an exercise to find a way to fix this.

Let us finish this presentation section with a couple more things. First, a simple aggregation. We want to group by `"Target Gender"` and `"Target Age"`, and compute the mean and the standard deviation (`"std"`) of `"Impressions"` and `"Spent"` within each grouping.

```
#31
agg_config = {
    "Impressions": ["mean", "std"],
    "Spent": ["mean", "std"],
}
df.groupby(["Target Gender", "Target Age"]).agg(agg_config)
```

We prepare a dictionary to use as the configuration. Then, we perform a grouping on the `"Target Gender"` and `"Target Age"` columns, and we pass our configuration dictionary to the `agg()` method. The output looks like this:

		Impressions		Spent	
		mean	std	mean	std
Target Gender	**Target Age**				
A	20-25	499999.245614	2.189918	217330.771930	204518.652595
	20-30	499999.465517	2.210148	252261.637931	228932.088945
	20-35	499998.564103	1.774006	218726.410256	215060.976707
	20-40	499999.459016	1.971241	255598.213115	222697.755231
	20-45	499999.574074	2.245346	216527.666667	190345.252888
...	...	...	...	...	...
M	45-50	499999.480769	2.128153	276112.557692	226975.008137
	45-55	499999.306122	2.053494	267137.938776	239249.474145
	45-60	499999.500000	1.984063	236623.312500	223464.578371
	45-65	499999.679245	1.503503	215634.528302	223308.046968
	45-70	499998.870370	1.822773	310267.944444	242353.980346

Let us do one more thing before we wrap this chapter up. We want to show you something called a **pivot table**. A pivot table is a way of grouping data, computing an aggregate value for each group, and displaying the result in table form. The pivot table is an essential tool for data analysis, so let us see a simple example:

```
#31
df.pivot_table(
    values=["Impressions", "Clicks", "Spent"],
    index=["Target Age"],
    columns=["Target Gender"],
    aggfunc="sum"
)
```

We create a pivot table that shows us the correlation between `"Target Age"` and `"Impressions"`, `"Clicks"`, and `"Spent"`. These last three will be subdivided according to `"Target Gender"`. The `aggfunc` argument specifies the aggregation function to use, it can be a function object, the name of a function, a list of functions, or a dictionary that maps column names to functions. In this case, we use `"sum"` (the default, if no function is specified is to compute the `mean`). The result is a new `DataFrame` containing the pivot table:

	Clicks			Impressions			Spent		
Target Gender	**A**	**F**	**M**	**A**	**F**	**M**	**A**	**F**	**M**
Target Age									
20-25	2460345	2355790	2954169	28499957	29999964	34999963	12387854	16271204	14605751
20-30	2254458	1742729	2133740	28999969	21999963	25999959	14631175	11435369	13184984
20-35	1323341	1735301	2926626	19499944	22499974	34999942	8530330	10987452	18383305
20-40	2304325	1987013	1975200	30499967	28499973	26999950	15591491	15490069	13806347
20-45	2402785	1667405	1790037	26999977	22499993	21999968	11692494	9064229	9623006

Figure 13.8: A pivot table

That brings us to the end of our data analysis project. We will leave you to discover more about the wonderful world of IPython, Jupyter, and data science. We strongly encourage you to get comfortable with the Notebook environment. It is much better than a console, it is practical and fun to use, and you can even create slides and documents with it.

Where do we go from here?

Data science is indeed a fascinating subject. As we said in the introduction, those who want to delve into its meanders need to have a solid foundation in mathematics and statistics. Working with data that has been interpolated incorrectly renders any result about it useless. The same goes for data that has been extrapolated incorrectly or sampled with the wrong frequency. To give you an example, imagine a population of individuals that are aligned in a queue. If, for some reason, the gender of that population alternated between male and female, the queue would look something like this: F-M-F-M-F-M-F-M-F...

If you sampled it, taking only the even elements, you would draw the conclusion that the population was made up only of males, while sampling the odd ones would tell you exactly the opposite.

Of course, this was just a silly example, but it is easy to make mistakes in this field, especially when dealing with big datasets where sampling is mandatory and, therefore, the quality of your analysis depends, first and foremost, on the quality of the sampling itself.

When it comes to data science and Python, these are the main tools you want to look at:

- **NumPy** (`https://www.numpy.org/`): This is the main package for scientific computing with Python. It contains a powerful N-dimensional array object, sophisticated (broadcasting) functions, tools for integrating C/C++ and Fortran code, useful linear algebra, the Fourier transform, random number capabilities, and much more.

- **scikit-learn** (`https://scikit-learn.org/`): This is one of the most popular machine learning libraries in Python. It has simple and efficient tools for data mining and data analysis, is accessible to everybody, and is reusable in various contexts. It is built on NumPy, SciPy, and Matplotlib.
- **pandas** (`https://pandas.pydata.org/`): This is an open-source, BSD-licensed library providing high-performance, easy-to-use data structures and data analysis tools. We have used it throughout this chapter.
- **IPython** (`https://ipython.org/`)/**Jupyter** (`https://jupyter.org/`): These provide a rich architecture for interactive computing.
- **Matplotlib** (`https://matplotlib.org/`): This is a Python 2D plotting library that produces publication-quality figures in a variety of hard-copy formats and interactive environments across platforms. Matplotlib can be used in Python scripts, the Python and IPython shell, a Jupyter Notebook, web application servers, and several graphical user interface toolkits.
- **Seaborn** (`https://seaborn.pydata.org/`): This is a Python data visualization library based on Matplotlib. It provides a high-level interface for drawing attractive and informative statistical graphics.
- **Numba** (`https://numba.pydata.org/`): This gives you the power to speed up your applications with high-performance functions written directly in Python. With a few annotations, array-oriented and math-heavy Python code can be just-in-time compiled to native machine instructions, similar in performance to C, C++, and Fortran, without having to switch languages or Python interpreters.
- **Bokeh** (`https://bokeh.pydata.org/`): This is a Python-interactive visualization library that targets modern web browsers for presentation. Its goal is to provide elegant, concise construction of novel graphics in the style of D3.js, but also deliver this capability with high-performance interactivity over large or streaming datasets.

Other than these single libraries, you can also find ecosystems, such as **SciPy** (`https://scipy.org/`) and the aforementioned **Anaconda** (`https://anaconda.org/`), that bundle several different packages to give you something that just works in an "out-of-the-box" fashion.

Installing all these tools and their several dependencies is hard on some systems, so we suggest that you try out ecosystems as well to see whether you are comfortable with them. It may be worth it.

Summary

In this chapter, we talked about data science. Rather than attempting to explain anything about this broad subject, we delved into a project. We familiarized ourselves with the Jupyter Notebook, and with different libraries, such as `pandas`, `Matplotlib`, and `NumPy`.

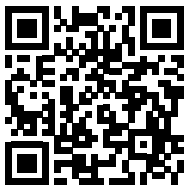
Of course, having to compress all this information into one single chapter means we could only touch briefly on the subjects we presented. We hope the project we have worked through together has been comprehensive enough to give you an idea of the workflow to follow when working in this field.

The next chapter is dedicated to API development.

Join our community on Discord

Join our community's Discord space for discussions with the authors and other readers:

`https://discord.com/invite/uaKmaz7FEC`



14

Introduction to API Development

> *"The one goal of compassionate communication is to help others suffer less."*
>
> *– Thich Nhat Hanh*

In this chapter, we are going to learn about the concept of **Application Programming Interface**, or **API**.

We are going to discuss the following:

- The HTTP protocol
- Introduction to API design
- A complete API example

We are going to briefly touch on the HTTP protocol, as it is the infrastructure upon which we will build the API. Moreover, since the framework we are going to use, **FastAPI**, leverages Type Hinting extensively, you may want to make sure you have read *Chapter 12, Introduction to Type Hinting*, as a prerequisite.

After a short general introduction to APIs, we are going to show you a railway project, which you can find in its complete state in the source code for this chapter, along with its requirements and a README file that explains all you need to know to run the API and query it.

FastAPI has proven to be the optimal choice for this project. Thanks to its capabilities, we have been able to create an API with clean, concise, and expressive code. We believe it to be a good starting point for you to explore and expand on.

As a developer, it is quite likely that you will have to work on APIs, at some point in your career. Technology and frameworks evolve all the time, so we recommend that you also focus on the theoretical concepts we are going to expose, as that knowledge will help you be less dependent on any particular framework or library.

Let us start with HTTP.

The Hypertext Transfer Protocol

The **World Wide Web** (**WWW**), or simply the **Web**, is a way of accessing information using the **Internet**. The Internet is a vast network of networks, a networking infrastructure. Its purpose is to connect billions of devices together, all around the globe, so that they can communicate with one another. Information travels through the Internet in a rich variety of languages, called **protocols**, that allow different devices to share content.

The Web is an information-sharing model, built on top of the Internet, which employs the **Hypertext Transfer Protocol** (**HTTP**) as a basis for data communication. The Web, therefore, is just one of several ways information can be exchanged over the Internet; email, instant messaging, news groups, and so on, all rely on different protocols.

How does HTTP work?

HTTP is an asymmetric **request-response client-server** protocol. An HTTP client – for example, your web browser – sends a request message to an HTTP server. The server, in turn, returns a response message. HTTP is primarily a **pull-based protocol**, which means the client pulls information from the server, rather than the server pushing it to the client. There are techniques, implemented over HTTP, that simulate push-based behavior, for example, long polling, WebSockets, and HTTP/2 Server Push. Despite these, the foundation of HTTP remains a pull-based protocol, where it is the client that initiates the requests. Look at the diagram in *Figure 14.1*:

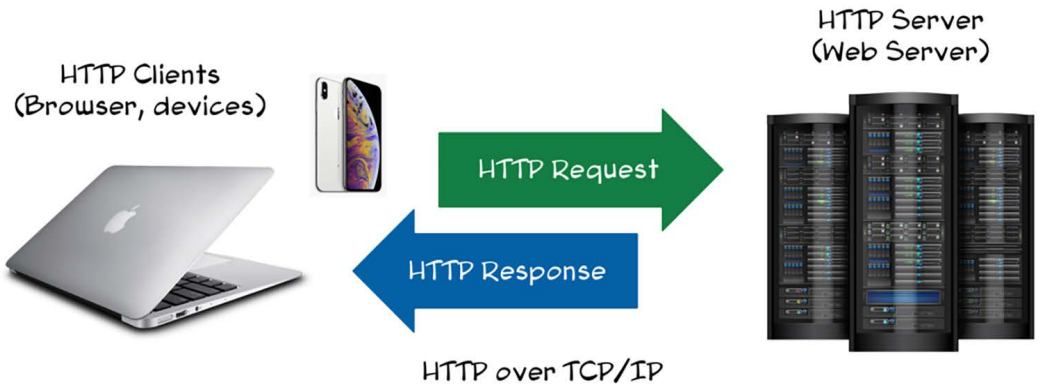


Figure 14.1: A simplified depiction of the HTTP protocol

HTTP is transmitted via the **Transmission Control Protocol/Internet Protocol (TCP/IP)**, which provides the tools for a reliable communication exchange over the Internet.

An important feature of the HTTP protocol is that it is **stateless**. This means that the current request has no knowledge about what happened in previous requests. This technical limitation exists for good reasons, but it is easy to overcome. In practice, most websites offer the ability to "log in" and the illusion of carrying a state from page to page. When a user logs in to a website, a token of user information is saved (most often on the client side, in special files called **cookies**) so that each request the user makes carries the means for the server to recognize the user and provide a custom interface by showing their name, keeping their basket populated, and so on.

HTTP defines a set of methods—also known as *verbs*—to indicate the desired action to be performed on a given resource. Each of them is different, but some of them share some common features. In particular, the ones we will use in our API are as follows:

- **GET**: The `GET` method requests a representation of the specified resource. Requests using `GET` should only retrieve data.
- **POST**: The `POST` method is used to submit an entity to the specified resource, often causing a change in state or side effects on the server.
- **PUT**: The `PUT` method requests that the target resource creates or updates its state with the state defined by the representation enclosed in the request.
- **DELETE**: The `DELETE` method requests that the target resource delete its state.

Other methods are `HEAD`, `CONNECT`, `OPTIONS`, `TRACE`, and `PATCH`. For a comprehensive explanation of all of these methods, please refer to `https://developer.mozilla.org/en-US/docs/Web/HTTP`.

The API we are going to write works over HTTP, which means we will write code to perform and handle HTTP requests and responses. We will not keep prepending "HTTP" to the terms "request" and "response" from now on, as we trust there will not be any confusion.

Response status codes

One thing to know about HTTP responses is that they include a status code, which expresses the outcome of the request in a concise way. Status codes consist of a number and a brief description, for example, *404 Not Found*. You can check the complete list of HTTP status codes at `https://developer.mozilla.org/en-US/docs/Web/HTTP/Status`.

Status codes are classified in this way:

- 1xx informational response: The request was received, continuing process.
- 2xx successful: The request was successfully received, understood, and accepted.
- 3xx redirection: Further action needs to be taken to complete the request.
- 4xx client error: The request contains bad syntax or cannot be fulfilled.
- 5xx server error: The server failed to fulfill a valid request.

When consuming the API, we will receive status codes in the responses, so it is important that you at least have an idea about what they mean.

APIs — An introduction

Before we delve into the details of this chapter's specific project, let us spend a moment talking about APIs in general.

What is an API?

As we mentioned at the beginning of the chapter, API stands for **Application Programming Interface**. An API is a set of rules, protocols, and tools for building software and applications. It acts as a connection layer between computers, or computer programs. In contrast, user interfaces provide a bridge between computers and people.

An API is normally accompanied by a *specification document*, or *standard*, which serves as a blueprint that outlines how software components are meant to interact. A system that meets the specification is said to implement, or expose, the API. The term API can describe both the implementation and the specification.

In essence, an API defines the methods and data formats that developers can use to interact with a program, a web service, or any other software.

Broadly speaking, there are two types of APIs:

- Web APIs: Accessible over the Internet, they are often used to enable web applications to interact with each other or with backend servers. They are the backbone of web development, enabling functionalities such as fetching data from a server, posting data, or integrating with third-party services like media platforms, payment gateways, and so on.
- Frameworks and software libraries: These provide a set of functions and procedures that perform specific tasks, and help speed up application development by providing building blocks to the developers.

In this chapter, we will be focusing on Web APIs.

An API is normally made of different parts. These are known by different names, the most common of which are *methods*, *subroutines*, or *endpoints* (we will call them endpoints in this chapter). When we use these parts, the technical term for this is *calling* them.

The API specification instructs you on how to call each endpoint, what type of requests to make, which parameters and headers to pass, which addresses to reach, and so on.

What is the purpose of an API?

There are several reasons to introduce an API into a system. One we have already mentioned is to create the means for different applications to communicate.

Another important reason is to give access to a system by providing a layer through which the external world can communicate with the system itself.

The API layer takes care of security by performing the **authentication** and **authorization** of users, as well as **validation** of all the data that is exchanged in the communications.

Authentication means the system can validate user credentials to unequivocally identify them. *Authorization* means the system can verify what a user has access to.

Users, systems, and data are checked and validated at the border, and if they pass the check, they can interact with the rest of the system (through the API).

This mechanism is conceptually like landing at an airport and having to show the border control our passports to be able to interact with the system, which is the country we landed in.

The fact that the API layer hides the internals of the systems from the outside world provides another benefit: if the internal system changes, in terms of technology, languages, or even workflows, the API can adapt the way it interfaces to it, but still provide a consistent interface to the public side. If we put a letter into a letterbox, we do not need to know or control how the postal service will deal with it, as long as the letter arrives at the destination. So, the interface (the letterbox) is kept consistent, while the other side (the mail carrier, their vehicles, technology, workflows, and so on) is free to change and evolve.

It should not be surprising that virtually any electronic device we own today, that is connected to the Web, is talking to a (potentially wide) range of APIs to perform its tasks.

API protocols

There are several types of API. They can be open to the public, or private. They can provide access to data, services, or both. APIs can be written and designed using different methods and standards, and they can employ different protocols.

These are the most common protocols:

- **Hypertext Transfer Protocol/Secure (HTTP/HTTPS)**: The foundation of data communication for the Web.
- **Representational State Transfer (REST)**: Technically not a protocol, but rather a type of architecture built over HTTP, APIs designed in this style are called RESTful APIs. They are stateless and capable of leveraging data caching.
- **Simple Object Access Protocol (SOAP)**: A well-established protocol for building web services, its messages are normally XML-formatted, and its specification is quite strict, which is why this protocol is suitable for situations that require high security standards and transactional reliability.
- **GraphQL**: A query language for APIs that employs a type system to define the data. Unlike REST, GraphQL uses a single endpoint to allow clients to fetch only the data they need.
- **WebSocket**: Ideal for applications that require bidirectional communication between client and server, as well as real-time data updates. They provide full-duplex communication over a single TCP connection.
- **Remote Procedural Call (RPC)**: It allows programmers to execute code on the server side by remotely calling a procedure (hence the name). These of APIs are tightly coupled with the server implementation, so they are usually not made for public consumption.

API data-exchange formats

We said that an API is an interface between at least two computer systems. It would be quite impractical, when interfacing with other systems, to have to shape the data into whatever format they implement. Therefore, the API, which provides the communication layer between systems, specifies not only the communication protocols but also which formats can be adopted for the data exchanges.

The most common data-exchange formats today are **JSON**, **XML**, and **YAML**. We saw JSON in *Chapter 8, Files and Data Persistence*, and we will use it as the format for the API of this chapter too. JSON is widely adopted today by many APIs, and many frameworks provide the ability to translate data from and to JSON, out of the box.

The railway API

Now that we have a working knowledge of what an API is, let us turn to something more concrete.

Before we show you the code, allow us to stress that this code is not production-ready, as that would have been too long and needlessly complex for a book's chapter. However, this code is fully functional, and it should provide you with a good starting point to learn more, especially if you experiment with it. We will leave suggestions on how to do so at the end of this chapter.

We have a database with some entities that model a railway application. We want to allow an external system to perform **CRUD** operations on the database, so we are going to write an API to serve as the interface to it.

CRUD stands for **Create**, **Read**, **Update**, and **Delete**. These are the four basic database operations. Many HTTP services also model CRUD operations through REST or REST-like APIs.

Let us start by looking at the project files, so you will have an idea of where things are. You can find them in the folder for this chapter, in the source code:

```
$ tree -a api_code
api_code
├── .env.example
├── api
│   ├── __init__.py
│   ├── admin.py
│   ├── config.py
```

```
│   ├── crud.py
│   ├── database.py
│   ├── deps.py
│   ├── models.py
│   ├── schemas.py
│   ├── stations.py
│   ├── tickets.py
│   ├── trains.py
│   ├── users.py
│   └── util.py
├── dummy_data.py
├── main.py
├── queries.md
└── train.db
```

Within the `api_code` folder, you can find all the files belonging to the FastAPI project. The main application module is `main.py`. We have left the `dummy_data.py` script in the code, which you can use to generate a new `train.db`, the database file. Make sure you read the `README.md` in this chapter's folder for instructions on how to use it. We have also collected a list of queries to the API for you to copy and try out, in `queries.md`.

Within the `api` package, we have the application modules. The database models are in `models.py`, and the schemas used to describe them to the API are in `schemas.py`. The other modules' purposes should be evident from their names: `users.py`, `stations.py`, `tickets.py`, `trains.py`, and `admin.py` all contain the definitions of the corresponding endpoints of the API. `util.py` contains some utility functions; `deps.py` defines the dependency providers; `config.py` holds the configuration settings; `crud.py` contains the functions that perform CRUD operations on the database and, finally, `.env.example` is a template for you to create a `.env` file to provide settings to your application.

In software engineering, **dependency injection** is a design pattern in which an object receives other objects that it depends on, called dependencies. The software responsible for constructing and injecting those dependencies is known as the *injector*, or *provider*. Hence, a dependency provider is a piece of software that creates and provides a dependency, so that other parts of the software can use it without having to take care of creating it, setting it up, and disposing of it. To learn more about this pattern, please refer to this Wikipedia page:

`https://en.wikipedia.org/wiki/Dependency_injection`

Modeling the database

When preparing the entity-relationship schema for this project, we sought to design something interesting and, at the same time, simple and contained. This application considers four entities: *Stations*, *Trains*, *Tickets*, and *Users*. A Train is a journey from one station to another one. A Ticket is a connection between a Train and a User. Users can be passengers or administrators, according to what they are supposed to be able to do with the API.

In *Figure 14.2*, you can see the **entity relationship** (**ER**) model of the database. It describes the four entities and how they relate to one another:

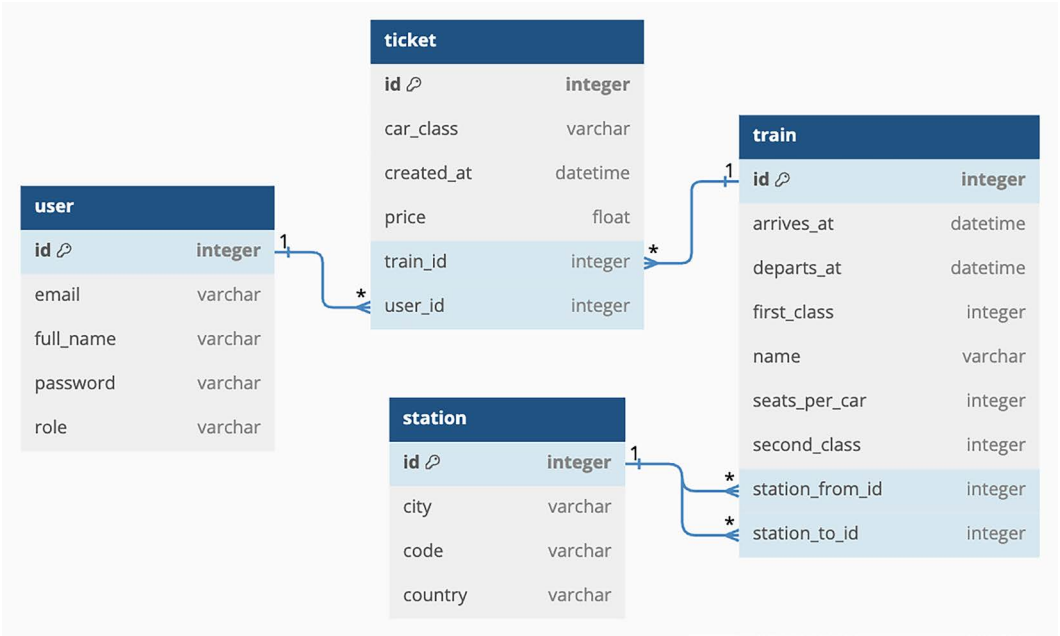


Figure 14.2: ER model of the database

We have defined the database models using SQLAlchemy, and we have chosen SQLite as the DBMS, for simplicity.

If you skipped *Chapter 8, Files and Data Persistence*, this would be a good moment to read it, as it will provide you with a foundation to understand the models in this chapter's project.

Let us see the `models` module:

```
# api_code/api/models.py
import hashlib
import os
import secrets
from enum import StrEnum, auto

from sqlalchemy import (
    DateTime,
    Enum,
    ForeignKey,
    Unicode,
)
from sqlalchemy.orm import mapped_column, relationship, Mapped

from .database import Base

UNICODE_LEN = 128
SALT_LEN = 64

# Enums
class Classes(StrEnum):
    first = auto()
    second = auto()

class Roles(StrEnum):
    admin = auto()
    passenger = auto()
```

As usual, at the top of the module, we import all that is necessary. We then define a couple of variables to indicate the default length of Unicode fields (`UNICODE_LEN`) and the length of the salt used to hash passwords (`SALT_LEN`).

For a refresher on what a salt is, please refer to *Chapter 9, Cryptography and Tokens*.

We also define two enumerations: `Classes` and `Roles`, which will be used in the models' definitions. We used the `StrEnum` class as a base, which was introduced in Python 3.11, and makes it possible to compare its members directly to strings. The `auto()` function automatically generates values for `Enum` attributes. For `StrEnum`, it will set the value to the lowercase version of the attribute name.

Let us see the definition of the `Station` model:

```
# api_code/api/models.py
class Station(Base):
    __tablename__ = "station"

    id: Mapped[int] = mapped_column(primary_key=True)
    code: Mapped[str] = mapped_column(
        Unicode(UNICODE_LEN), unique=True
    )
    country: Mapped[str] = mapped_column(Unicode(UNICODE_LEN))
    city: Mapped[str] = mapped_column(Unicode(UNICODE_LEN))

    departures: Mapped[list["Train"]] = relationship(
        foreign_keys="[Train.station_from_id]",
        back_populates="station_from",
    )
    arrivals: Mapped[list["Train"]] = relationship(
        foreign_keys="[Train.station_to_id]",
        back_populates="station_to",
    )

    def __repr__(self):
        return f"<{self.code}: id={self.id} city={self.city}>"

    __str__ = __repr__
```

The `Station` model is quite straightforward. There are a few attributes: `id` acts as the primary key, and then we have `code`, `country`, and `city`, which (when combined) tell us all we need to know about a station. There are two relationships that link station instances to all the trains departing from, and arriving to, them. The rest of the code defines the `__repr__()` method, which provides a string representation for instances, and whose implementation is also assigned to `__str__()`, so the output will be the same whether we call `str(station_instance)` or `repr(station_instance)`. This technique is quite commonly adopted to prevent code repetition.

Notice that we defined a unique constraint on the `code` field to ensure that no two stations with the same code can exist in the database. Big cities like Rome, London, and Paris have more than one train station, so the fields `city` and `country` can be the same for stations located in the same city, but each of them must have its own unique `code`.

Following that, we find the definition of the `Train` model:

```
# api_code/api/models.py
class Train(Base):
    __tablename__ = "train"

    id: Mapped[int] = mapped_column(primary_key=True)
    name: Mapped[str] = mapped_column(Unicode(UNICODE_LEN))

    station_from_id: Mapped[int] = mapped_column(
        ForeignKey("station.id")
    )
    station_from: Mapped["Station"] = relationship(
        foreign_keys=[station_from_id],
        back_populates="departures",
    )

    station_to_id: Mapped[int] = mapped_column(
        ForeignKey("station.id")
    )
    station_to: Mapped["Station"] = relationship(
        foreign_keys=[station_to_id],
        back_populates="arrivals",
    )

    departs_at: Mapped[DateTime] = mapped_column(
        DateTime(timezone=True)
    )
    arrives_at: Mapped[DateTime] = mapped_column(
        DateTime(timezone=True)
    )

    first_class: Mapped[int] = mapped_column(default=0)
```

```
    second_class: Mapped[int] = mapped_column(default=0)
    seats_per_car: Mapped[int] = mapped_column(default=0)

    tickets: Mapped[list["Ticket"]] = relationship(
        back_populates="train"
    )

    def __repr__(self):
        return f"<{self.name}: id={self.id}>"

    __str__ = __repr__
```

In the `Train` model, we find all the attributes we need to describe a train instance, plus a handy relationship, `tickets`, that gives us access to all the tickets that have been created against a train. The `first_class` and `second_class` fields hold how many first- and second-class cars a train has.

We also added relationships to station instances: `station_from` and `station_to`. These allow us to fetch the station instances as objects, instead of only having access to their IDs.

Next, the `Ticket` model:

```
# api_code/api/models.py
class Ticket(Base):
    __tablename__ = "ticket"

    id: Mapped[int] = mapped_column(primary_key=True)
    created_at: Mapped[DateTime] = mapped_column(
        DateTime(timezone=True)
    )

    user_id: Mapped[int] = mapped_column(ForeignKey("user.id"))
    user: Mapped["User"] = relationship(
        foreign_keys=[user_id], back_populates="tickets"
    )

    train_id: Mapped[int] = mapped_column(ForeignKey("train.id"))
    train: Mapped["Train"] = relationship(
        foreign_keys=[train_id], back_populates="tickets"
    )
```

```
    price: Mapped[float] = mapped_column(default=0)
    car_class: Mapped[Enum] = mapped_column(Enum(Classes))

    def __repr__(self):
        return (
            f"<id={self.id} user={self.user} train={self.train}>"
        )

    __str__ = __repr__
```

A `Ticket` has some properties too and includes two relationships: `user` and `train`, which point to the user who bought the ticket, and to the train the ticket is for, respectively.

Notice how we have used the `Classes` enumeration in the definition of the `car_class` attribute. This translates to an enumeration field in the database schema definition.

Finally, the `User` model:

```
# api_code/api/models.py
class User(Base):
    __tablename__ = "user"

    pwd_separator = "#"

    id: Mapped[int] = mapped_column(primary_key=True)
    full_name: Mapped[str] = mapped_column(
        Unicode(UNICODE_LEN), nullable=False
    )
    email: Mapped[str] = mapped_column(
        Unicode(2 * UNICODE_LEN), unique=True
    )
    password: Mapped[str] = mapped_column(
        Unicode(2 * UNICODE_LEN)
    )
    role: Mapped[Enum] = mapped_column(Enum(Roles))

    tickets: Mapped[list["Ticket"]] = relationship(
        back_populates="user"
```

```
    )

    def is_valid_password(self, password: str):
        """Tell if password matches the one stored in DB."""
        salt, stored_hash = self.password.split(
            self.pwd_separator
        )
        _, computed_hash = _hash(
            password=password, salt=bytes.fromhex(salt)
        )
        return secrets.compare_digest(stored_hash, computed_hash)

    @classmethod
    def hash_password(cls, password: str, salt: bytes = None):
        salt, hashed = _hash(password=password, salt=salt)
        return f"{salt}{cls.pwd_separator}{hashed}"

    def __repr__(self):
        return (
            f"<{self.full_name}: id={self.id} "
            f"role={self.role.name}>"
        )

    __str__ = __repr__
```

The `User` model defines some properties for each user. Note how here we have another enumeration used for the user's role. A user can either be a passenger or an admin. This will allow us to present you with a simple example of how to write an endpoint that allows access only to authorized users.

There are a couple of methods on the `User` model that are used to hash and validate passwords. You might recall from *Chapter 9, Cryptography and Tokens*, that passwords should never be stored in a database in plain text (which means, as they are). So, in our API, when saving a password for a user, we create a hash and store it alongside the salt that was used for the encryption. In the source code for the book, you will find, at the end of this module, the implementation of the `_hash()` function, which we have omitted here for brevity.

Main setup and configuration

Now that we understand the database models, let us inspect the main entry point of the application:

```
# api_code/main.py
from api import admin, config, stations, tickets, trains, users
from fastapi import FastAPI

settings = config.Settings()

app = FastAPI()
app.include_router(admin.router)
app.include_router(stations.router)
app.include_router(trains.router)
app.include_router(users.router)
app.include_router(tickets.router)

@app.get("/")
def root():
    return {
        "message": (
            f"Welcome to version {settings.api_version} "
            f"of our API"
        )
    }
```

This is all the code in the `main.py` module. It imports the various endpoint modules and includes their routers in the main app. By including a router in the main app, we enable the application to serve all the endpoints declared using that specific router. We will explain what routers are later in the chapter.

There is only one endpoint in the main module, which serves as a greeting message. An endpoint is a simple function – in this case, `root()` – that contains the code to be executed when a request is made against it. When and how this function will be invoked depends on the decorator(s) applied to the function. In this case, the `app.get()` decorator instructs the API to serve this endpoint when called with a GET request. The decorator accepts an argument to specify the URL path on which the endpoint will be served. Here, we use `"/"` to specify that this endpoint will be found at the root, which is the base URL on which the app is running.

If this API were served at the base URL `http://localhost:8000`, this endpoint would be called when we requested either `http://localhost:8000` or `http://localhost:8000/` (notice the difference is in the trailing slash).

Application settings

Within the greeting message from the last snippet of code, there is a variable, `api_version`, taken from the `settings` object. All frameworks allow for a collection of settings to be injected into the application to configure its behavior. We did not really need to use settings in this example project—we could have just hardcoded those values in the main module—but we thought it was worth showing you how they work:

```
# api_code/api/config.py
from pydantic_settings import BaseSettings, SettingsConfigDict

class Settings(BaseSettings):
    model_config = SettingsConfigDict(env_file=".env")

    secret_key: str
    debug: bool
    api_version: str
```

Settings are defined within a Pydantic model (`https://github.com/pydantic/pydantic`). **Pydantic** is a library that provides data validation using Python-type annotations. Older versions of Pydantic also provided settings management, but that feature has been extracted into a separate library called `pydantic-settings` (`https://github.com/pydantic/pydantic-settings`), which also adds additional settings management capabilities. In this case, we have three pieces of information within the settings:

- `secret_key`: Used to sign and verify JSON Web Tokens (JWTs).
- `debug`: When set to `True`, it instructs the SQLAlchemy engine to log verbosely, which is helpful to debug queries.
- `api_version`: The version of the API. We do not really make use of this information, apart from displaying it in the greeting message, but normally the version plays an important role because it is tied to a specific API specification.

FastAPI plucks these settings from a `.env` file, as specified when we create the `SettingsConfigDict` instance. Here is how that file looks:

```
# api_code/.env
SECRET_KEY="018ea65f62337ed59567a794b19dcaf8"
DEBUG=false
API_VERSION=2.0.0
```

For this to work, FastAPI needs help from a library called `python-dotenv`. It is part of this chapter's requirements, so if you have installed them in your virtual environment, you are all set.

Station endpoints

We are going to explore some FastAPI endpoints. Because this API is CRUD-oriented, there is some repetition in the code. We will therefore show you one example for each of the CRUD operations, and we will do so by using the `Station` endpoints examples. Please refer to the source code to explore the endpoints related to the other models. You will find that they all follow the same patterns and conventions. The main difference is that they relate to different database models.

Reading data

Let us start our exploration with a GET request. In this case, we are going to get all the stations in the database.

```
# api_code/api/stations.py
from typing import Optional

from fastapi import (
    APIRouter,
    Depends,
    HTTPException,
    Response,
    status,
)
from sqlalchemy.orm import Session

from . import crud
from .deps import get_db
```

```
from .schemas import Station, StationCreate, StationUpdate, Train

router = APIRouter(prefix="/stations")

@router.get("", tags=["Stations"])
def get_stations(
    db: Session = Depends(get_db), code: Optional[str] = None
) -> list[Station]:
    return crud.get_stations(db=db, code=code)
```

Within the `stations.py` module, we start by importing the necessary objects from the `typing` module, and from `fastapi`. We also import `Session` from `sqlalchemy`, and a few other tools from the local codebase.

The endpoint `get_stations()` is decorated with a `router` object, instead of `app` like in the main file. `APIRouter` can be thought of as a mini `FastAPI` class, in that it takes all the same arguments. We declare `router` and assign a prefix to it (`"/stations"`, in this case), which means all functions decorated with this router become endpoints that can be called at addresses that start with `http://localhost:8000/stations`. In this case, the empty string fed to the `router.get()` method instructs the app to serve this endpoint on the root URL for this router, which will be the concatenation of the base URL and the router prefix, as explained above.

FastAPI provides a couple of alternative ways to specify the type of data returned from an endpoint. One is to pass a `response_model` argument to the decorator. In our case, though, it is enough to specify the return value of the function using type annotations. For this endpoint, we return a list of `Station` instances. We will see their implementation shortly.

The `tags` argument is used for documentation purposes.

The function itself takes some arguments, which are a database session, `db`, and an optional string, `code`, which, when specified, will instruct the endpoint to serve only the stations whose `code` field matches the one provided.

A few things to notice:

- Data coming with the request, such as query parameters, is specified in the endpoint declaration. If the endpoint function requires data to be sent in the body of the request, this is specified using Pydantic models (in this project, they are defined in the `schemas.py` module).

- Whatever an endpoint returns becomes the body of the response. FastAPI will try to serialize the returned data to JSON. However, when the response model is set, serialization goes first through the Pydantic model specified in `response_model`, and then from the Pydantic model to JSON.
- To use a database session in the body of an endpoint, we use a dependency provider, which, in this case, is specified using the `Depends` class, to which we pass the `get_db()` function. This function yields a local database session and closes it when the endpoint call terminates.
- We use the `Optional` class, from the `typing` module, to specify that parameters are optional in a request.

The body of the `get_stations()` function simply calls the function of the same name from the `crud` module and returns the resulting value. All the functions that regulate the interaction with the database live in the `crud.py` module.

This was a design choice that should make this code easier to reuse and test. Moreover, it simplifies reading the entry point code. Let us see the body of `get_stations()` in the `crud.py` module:

```
# api_code/api/crud.py
from datetime import UTC, datetime
from sqlalchemy import delete, select, update
from sqlalchemy.orm import Session, aliased
from . import models, schemas

def get_stations(db: Session, code: str | None = None):
    stm = select(models.Station)
    if code is not None:
        stm = stm.where(models.Station.code.ilike(code))
    return db.scalars(stm).all()
```

Notice how similar this function's signature is to the one for the endpoint that calls it. `get_stations()` selects and returns all instances of `Station`, optionally filtered by `code` (in case it is not `None`).

To start the API, activate your virtual environment and run the following command from within the `api_code` folder:

```
$ uvicorn main:app --reload
```

Uvicorn is a lightning-fast **ASGI server**, built on `uvloop` and `httptools`. It works seamlessly with both normal and asynchronous functions.

From the ASGI documentation page (`https://asgi.readthedocs.io/`):

> **ASGI** *(***Asynchronous Server Gateway Interface***) is a spiritual successor to* **WSGI** *(***Web Server Gateway Interface***), intended to provide a standard interface between async-capable Python web servers, frameworks, and applications.*
>
> *Where WSGI provided a standard for synchronous Python apps, ASGI provides one for both asynchronous and synchronous apps, with a WSGI backwards-compatibility implementation and multiple servers and application frameworks.*

For this chapter's project, we have chosen to write synchronous code as the asynchronous equivalent would have only made the code more difficult to understand.

If you are comfortable writing asynchronous code, please refer to the FastAPI documentation (`https://fastapi.tiangolo.com`) to learn how to write asynchronous endpoints.

The `--reload` flag in the `uvicorn` command above configures the server to automatically reload whenever a file is saved. It is optional, but quite useful for saving time when you are working on the API source code.

If we called the `get_stations()` endpoint, this is what we would see:

```
$ http http://localhost:8000/stations
HTTP/1.1 200 OK
content-length: 702
content-type: application/json
date: Thu, 04 Apr 2024 09:46:29 GMT
server: uvicorn

[
    {
        "city": "Rome",
        "code": "ROM",
        "country": "Italy",
        "id": 0
```

```
    },
    {
        "city": "Paris",
        "code": "PAR",
        "country": "France",
        "id": 1
    },
    ... some stations omitted ...
    {
        "city": "Sofia",
        "code": "SFA",
        "country": "Bulgaria",
        "id": 11
    }
]
```

Notice the command we are using to call the API: `http`. This is a command that comes with the **Httpie** utility.

You can find Httpie at `https://httpie.io`. Httpie is a user-friendly command-line HTTP client for the API era. It comes with JSON support, syntax highlighting, persistent sessions, wget-like downloads, plugins, and more. There are other tools to perform requests, such as **curl**. The choice is up to you, as it makes no difference which tool you use to make requests from the command line.

The API is served by default at `http://localhost:8000`. You can add arguments to the `uvicorn` command to customize this, if you so desire.

The first few lines of the response are information from the API engine. We learn the protocol used was HTTP1.1, and that the request succeeded (status code *200 OK*). We have info on the content length, and its type, which is JSON. Finally, we get a timestamp and the type of server. We are going to omit the part of this information that just repeats, from now on.

The body of the response is a list of `Station` instances, in their JSON representation, thanks to `list[Station]` type annotation, which we indicated in the function signature.

If we were to search by `code`, for example, the London station, we could use the following command:

```
$ http http://localhost:8000/stations?code=LDN
```

The above command uses the same URL as before but adds the code query parameter (separated from the URL path with a ?). The result is as follows:

```
$ http http://localhost:8000/stations?code=LDN
HTTP/1.1 200 OK
...
[
    {
        "city": "London",
        "code": "LDN",
        "country": "UK",
        "id": 2
    }
]
```

Notice how we got one match, which corresponds to the London station, but still, it is returned as a list, as indicated by the type annotation for this endpoint.

Let us now explore an endpoint dedicated to fetching a single station by ID:

```
# api_code/api/stations.py
@router.get("/{station_id}", tags=["Stations"])
def get_station(
    station_id: int, db: Session = Depends(get_db)
) -> Station:
    db_station = crud.get_station(db=db, station_id=station_id)
    if db_station is None:
        raise HTTPException(
            status_code=404,
            detail=f"Station {station_id} not found.",
        )
    return db_station
```

For this endpoint, we configure the router to accept GET requests, at the URL `http://localhost:8000/stations/{station_id}`, where `station_id` will be an integer. Hopefully, the way URLs are constructed is starting to make sense for you. There is the base part, `http://localhost:8000`, then the prefix for the router, `/stations`, and finally, the specific URL information that we feed to each endpoint, which in this case is `/{station_id}`.

Let us fetch the Kyiv station, with ID 3:

```
$ http http://localhost:8000/stations/3
HTTP/1.1 200 OK
...
{
    "city": "Kyiv",
    "code": "KYV",
    "country": "Ukraine",
    "id": 3
}
```

Notice how this time we got back an object by itself, instead of it being wrapped in a list like it was in the `get_stations()` endpoint. This is in accordance with the type annotation for this endpoint, which is set to `Station`, and it makes sense, as we are fetching a single object by ID.

The `get_station()` function takes the `station_id`, type-annotated as an integer, and the usual `db` session object. Using type annotations to specify parameters allows FastAPI to do data validation on the type of the arguments we use when calling an endpoint.

If we were to pass a non-integer value for `station_id`, this would happen:

```
$ http http://localhost:8000/stations/kyiv
HTTP/1.1 422 Unprocessable Entity
...
{
    "detail": [
        {
            "input": "kyiv",
            "loc": [
                "path",
                "station_id"
            ],
            "msg": "Input should be a valid integer, …",
            "type": "int_parsing",
            "url": "https://errors.pydantic.dev/2.6/v/int_parsing"
        }
    ]
}
```

Notice we had to abridge the error message due to its length. FastAPI responds with useful information: `station_id`, from the path, is not a valid integer. Notice also that the status code is *422 Unprocessable Entity*, as opposed to *200 OK*, this time. In general, errors in the four hundreds (*4xx*) express client errors, while errors in the five hundreds (*5xx*) express server errors. In this case, we are making a call using an incorrect URL (we are not using an integer). Therefore, it is an error on the client side. Other API frameworks would return a simple *400 Bad Request* status code in the same scenario, but FastAPI returns *422 Unprocessable Entity*, which is oddly specific. It is easy though, in FastAPI, to customize which status would be returned upon a bad request; there are examples in the official documentation.

Let us see what happens when we try to fetch a station with an ID that does not exist:

```
$ http http://localhost:8000/stations/100
HTTP/1.1 404 Not Found
...
{
    "detail": "Station 100 not found."
}
```

This time the URL is correct, in that `station_id` is an integer; however, there is no station with ID 100. The API returns the *404 Not Found* status, as the response body tells us.

If you go back to the code of this endpoint, you will notice how straightforward its logic is: provided that the arguments passed are correct—in other words, they respect the type—it tries to fetch the corresponding station from the database by using another simple function from the `crud` module. If the station is not found, it raises an `HTTPException` with the desired status code (404) and a detail that will hopefully help the consumer understand what went wrong. If the station is found, then it is returned. The process of returning a JSON serialized version of objects is done automatically by FastAPI. The object retrieved from the database is a SQLAlchemy instance of the `Station` class (`models.Station`). That instance is fed to the Pydantic `Station` class (`schemas.Station`), which is used to produce a JSON representation that is then returned by the endpoint.

This might seem complicated, but it is an excellent example of decoupling. FastAPI takes care of the workflow, and all we need to do is take care of the wiring: request parameters, response models, dependencies, and so on.

Creating data

Let us now see something a bit more interesting: how to create a station. First, the endpoint:

```
# api_code/api/stations.py
@router.post(
    "",
    status_code=status.HTTP_201_CREATED,
    tags=["Stations"],
)
def create_station(
    station: StationCreate, db: Session = Depends(get_db)
) -> Station:
    db_station = crud.get_station_by_code(
        db=db, code=station.code
    )
    if db_station:
        raise HTTPException(
            status_code=400,
            detail=f"Station {station.code} already exists.",
        )
    return crud.create_station(db=db, station=station)
```

This time, we instruct the router that we want to accept a POST request to the root URL (remember: base part, plus router prefix). We type-annotate the return to be `Station`, as the endpoint will be returning the newly created object, and we also specify the default status code for the response, which is `201 Created`.

The `create_station()` function takes the usual `db` session and a `station` object. The `station` object is created for us, behind the scenes. FastAPI takes the data from the body of the request and feeds it to the Pydantic schema `StationCreate`. That schema defines all the data we need to receive, and the result is the `station` object.

The logic in the body follows this flow: it tries to get a station using the code provided; if a station is found, we cannot create one with that data. The code field is defined to be unique. Therefore, creating a station with the same code would result in a database error. Hence, we return status code *400 Bad Request*, informing the caller that the station already exists. If the station is not found, we can instead proceed to create it and return it. Let us see the declaration of the Pydantic schemas involved:

```
# api_code/api/schemas.py
from pydantic import BaseModel, ConfigDict

class StationBase(BaseModel):
    code: str
    country: str
    city: str

class Station(StationBase):
    model_config = ConfigDict(from_attributes=True)
    id: int

class StationCreate(StationBase):
    pass
```

Note how we used inheritance to define the schemas. It is normal practice to have a base schema that provides functionalities common to all children. Then, each child specifies its needs separately. In this case, in the base schema, we have `code`, `country`, and `city`. When fetching stations, we also want to return the `id`, so we specify that in the `Station` class. Moreover, since this class is used to translate SQLAlchemy objects, we need to tell the model about it, and we do so by specifying the `model_config` attribute. Remember that SQLAlchemy is an **object-relational mapping** (**ORM**), so we need to tell the model to read the attributes of an object by setting `from_attributes=True`.

The `StationCreate` model does not need anything extra, so we simply use the `pass` instruction as a body.

Let us now see the CRUD functions for this endpoint:

```
# api_code/api/crud.py
def get_station_by_code(db: Session, code: str):
    return db.scalar(
        select(models.Station).where(
            models.Station.code.ilike(code)
        )
    )

def create_station(
    db: Session,
    station: schemas.StationCreate,
):
```

```
    db_station = models.Station(**station.model_dump())
    db.add(db_station)
    db.commit()
    return db_station
```

The `get_station_by_code()` function is fairly simple. It selects a `Station` object with a case-insensitive match on `code` (the "i" prefix in `ilike()` means case-insensitive).

There are other ways to perform a case-insensitive comparison, which do not involve using `ilike`. Those might be the right way to go when performance is important, but for this chapter's purpose, we found the simplicity of `ilike` to be exactly what we needed.

The `create_station()` function takes a `db` session and a `StationCreate` instance. First, we get the station data in the form of a Python dictionary (by calling `model_dump()`). We know all data must be there; otherwise, the endpoint would have already failed during the initial Pydantic validation stage.

Using the data from `station.model_dump()`, we create an instance of the SQLAlchemy `Station` model. We add it to the database, commit the transaction, and return it. Note that when we initially create the `db_station` object, it does not have an `id` attribute. The `id` is automatically assigned by the database engine when the row is inserted into the `stations` table (which happens when we call `db.commit()`). SQLAlchemy will automatically set the `id` attribute when we call `commit()`.

Let us see this endpoint in action. Notice how we need to specify `POST` to the `http` command, which allows us to send data, in JSON format, within the body of the request. Previous requests were of the GET type, which is the default type for the `http` command. Notice also that we have split the command over two lines due to the book's line length constraints:

```
$ http POST http://localhost:8000/stations \
code=TMP country=Temporary-Country city=tmp-city
HTTP/1.1 201 Created
...
{
    "city": "tmp-city",
    "code": "TMP",
    "country": "Temporary-Country",
    "id": 12
}
```

We successfully created a station. Let us now try again, but this time omitting the code, which is mandatory:

```
$ http POST http://localhost:8000/stations \
country=Another-Country city=another-city
HTTP/1.1 422 Unprocessable Entity
...
{
    "detail": [
        {
            "input": {
                "city": "another-city",
                "country": "Another-Country"
            },
            "loc": [
                "body",
                "code"
            ],
            "msg": "Field required",
            "type": "missing",
            "url": "https://errors.pydantic.dev/2.6/v/missing"
        }
    ]
}
```

As expected, we get a *422 Unprocessable Entity* status code again, because the Pydantic `StationCreate` model validation failed, and the response body tells us why: `code` is missing in the body of the request. It also provides a useful link to look up the error.

Updating data

The logic to update a station is a bit more complex. Let us go through it together. First, the endpoint:

```
# api_code/api/stations.py
@router.put("/{station_id}", tags=["Stations"])
def update_station(
    station_id: int,
    station: StationUpdate,
    db: Session = Depends(get_db),
):
```

```
    db_station = crud.get_station(db=db, station_id=station_id)

    if db_station is None:
        raise HTTPException(
            status_code=404,
            detail=f"Station {station_id} not found.",
        )
    else:
        crud.update_station(
            db=db, station=station, station_id=station_id
        )
        return Response(status_code=status.HTTP_204_NO_CONTENT)
```

The router is instructed to listen for a PUT request, which is the type you should use to modify a web resource. The URL terminates with the `station_id`, which identifies the station we want to update. The function takes the `station_id`, a Pydantic `StationUpdate` instance, and the usual `db` session.

We start by fetching the desired station from the database. If the station is not found in the database, we simply return a *404 Not Found* status code, as there is nothing to update. Otherwise, we update the station and return a *204 No Content* status code, which is the common way to respond to a PUT request. We could also have returned *200 OK*, but in that case, we should have returned the updated resource within the body of the response.

The Pydantic model for a station update is this:

```
# api_code/api/schemas.py
from typing import Optional

class StationUpdate(StationBase):
    code: Optional[str] = None
    country: Optional[str] = None
    city: Optional[str] = None
```

All properties are declared as `Optional` because we want to allow the caller to pass only what they wish to update.

Let us see the code for the CRUD function responsible for updating a station:

```
# api_code/api/crud.py
def update_station(
    db: Session, station: schemas.StationUpdate, station_id: int
):
    stm = (
        update(models.Station)
        .where(models.Station.id == station_id)
        .values(station.model_dump(exclude_unset=True))
    )
    result = db.execute(stm)
    db.commit()
    return result.rowcount
```

The `update_station()` function takes the necessary arguments to identify the station to update, and the station data that will be used to update the record in the database, plus the usual `db` session.

We build a statement using the `update()` helper from `sqlalchemy`. We use `where()` to filter the station by `id`, and we specify the new values by asking the Pydantic station object to give us a Python dictionary excluding anything that has not been passed to the call. This serves the purpose of allowing partial updates to be executed. If we omitted `exclude_unset=True` from the code, any argument that was not passed would end up in the dictionary, set to its default value (`None`).

Strictly speaking, we should use a PATCH request to do a partial update, but it is fairly common to use PUT for both complete and partial updates.

We execute the statement and return the number of rows affected by this operation. We do not use this information in the endpoint body, but it would be a nice exercise for you to do it. We will see how to make use of that information in the endpoint that deletes a station.

Let us use this endpoint on the station we created in the previous section, with ID 12:

```
$ http PUT http://localhost:8000/stations/12 \
code=SMC country=Some-Country city=Some-city
HTTP/1.1 204 No Content
...
```

We got what we expected. Let us verify that the update was successful:

```
$ http http://localhost:8000/stations/12
HTTP/1.1 200 OK
...
{
    "city": "Some-city",
    "code": "SMC",
    "country": "Some-Country",
    "id": 12
}
```

All three properties of the object with ID 12 have been changed. Let us now try a partial update:

```
$ http PUT http://localhost:8000/stations/12 code=xxx
HTTP/1.1 204 No Content
...
```

This time we only updated the station code. Let us verify again:

```
$ http http://localhost:8000/stations/12
HTTP/1.1 200 OK
...
{
    "city": "Some-city",
    "code": "xxx",
    "country": "Some-Country",
    "id": 12
}
```

As expected, only `code` was changed.

Deleting data

Finally, let us explore how to delete a station. As usual, let us start with the endpoint:

```python
# api_code/api/stations.py
@router.delete("/{station_id}", tags=["Stations"])
def delete_station(
    station_id: int, db: Session = Depends(get_db)
):
    row_count = crud.delete_station(db=db, station_id=station_id)
```

```
    if row_count:
        return Response(status_code=status.HTTP_204_NO_CONTENT)
    return Response(status_code=status.HTTP_404_NOT_FOUND)
```

To delete stations, we instruct the router to listen for a DELETE request. The URL is the same one we used to get a single station, as well as to update one. It is the HTTP verb we choose that triggers the right endpoint. The `delete_station()` function takes `station_id` and the `db` session.

Inside the body of the endpoint, we get the number of rows affected by the operation. In this case, if there is one, we return a *204 No Content* status code, which tells the caller that the deletion was successful. If no rows were affected, we return a *404 Not Found* status code. Notice that we could have written the update method exactly like this, making use of the number of affected rows, but we chose another approach there so that you had a different example to learn from.

Let us see the `CRUD` function:

```
# api_code/api/crud.py
def delete_station(db: Session, station_id: int):
    stm = delete(models.Station).where(
        models.Station.id == station_id
    )
    result = db.execute(stm)
    db.commit()
    return result.rowcount
```

This function makes use of the `delete()` helper from `sqlalchemy`. Similar to what we did for the update scenario, we create a statement that identifies a station by ID and instructs for its deletion. We execute the statement and return the number of affected rows.

Let us see this endpoint in action, on a successful scenario first:

```
$ http DELETE http://localhost:8000/stations/12
HTTP/1.1 204 No Content
...
```

We got a *204 No Content* status code, which tells us the deletion was successful. Let us verify it indirectly by trying to delete the station with ID `12` again. This time we expect the station to be gone, and a *404 Not Found* status code in return:

```
$ http DELETE http://localhost:8000/stations/12
HTTP/1.1 404 Not Found
...
```

As expected, we received a *404 Not Found* status code, which means a station with ID 12 was not found, proving that the first attempt to delete it was successful. There are a few more endpoints in the `stations.py` module, which you should check out.

The other endpoints we have written are there to create, read, update, and delete users, trains, and tickets. Apart from the fact that they act on different database and Pydantic models, they would not really bring any more insight to this exposition. Therefore, let us instead look at an example of how to authenticate a user.

User authentication

Authentication, in this project, is done via a JWT. Once again, please refer to *Chapter 9, Cryptography and Tokens*, for a refresher on JWTs.

Let us start from the authentication endpoint, in the `users.py` module:

```
# api_code/api/users.py
from .util import InvalidToken, create_token, extract_payload

@router.post("/authenticate", tags=["Auth"])
def authenticate(
    auth: Auth,
    db: Session = Depends(get_db),
    settings: Settings = Depends(get_settings),
):
    db_user = crud.get_user_by_email(db=db, email=auth.email)
    if db_user is None:
        raise HTTPException(
            status_code=status.HTTP_404_NOT_FOUND,
            detail=f"User {auth.email} not found.",
        )

    if not db_user.is_valid_password(auth.password):
        raise HTTPException(
            status_code=status.HTTP_401_UNAUTHORIZED,
            detail="Wrong username/password.",
        )

    payload = {
```

```
        "email": auth.email,
        "role": db_user.role.value,
    }
    return create_token(payload, settings.secret_key)
```

This router has the prefix `"/users"`. To authenticate a user, we need to make a POST request to this endpoint. It takes a Pydantic `Auth` schema, the usual `db` session, and the `settings` object, which is needed to provide the secret key that is used to create the token.

If the user is not found, we return a *404 Not Found* status code. If the user is found, but the password provided does not correspond to the one in the database record, we return status code *401 Unauthorized*. Finally, if the user is found and the password is correct, we create a token with two claims: `email` and `role`. We will use the role to perform authorization functions.

The `create_token()` function is a wrapper around `jwt.encode()` that also adds a couple of timestamps to the payload of the token. It is not worth showing that code here. Let us instead see the `Auth` model:

```
# api_code/api/schemas.py
class Auth(BaseModel):
    email: str
    password: str
```

We authenticate users with their email (which serves as the username) and password. That is why, in the SQLAlchemy `User` model, we have set up a uniqueness constraint on the `email` field. We need each user to have a unique username, and email is a commonly used field for this need.

Let us exercise this endpoint:

```
$ http POST http://localhost:8000/users/authenticate \
email="fabrizio.romano@example.com" password="f4bPassword"
HTTP/1.1 200 OK
...

"eyJhbGciOiJIUzI1NiIsInR5cCI6IkpXVCJ9....01GK4QyzZje8NKMzBBVckc"
```

We got a token back (abridged, in the snippet), so we can use it. The user we have authenticated is an admin, so we are going to show you how we could have written the endpoint to delete a station if we wanted to allow only admins to do so. Let us see the code:

```
# api_code/api/admin.py
from .util import is_admin

router = APIRouter(prefix="/admin")

def ensure_admin(settings: Settings, authorization: str):
    if not is_admin(
        settings=settings, authorization=authorization
    ):
        raise HTTPException(
            status_code=status.HTTP_403_FORBIDDEN,
            detail="You must be admin to access this endpoint.",
        )

@router.delete("/stations/{station_id}", tags=["Admin"])
def admin_delete_station(
    station_id: int,
    authorization: Optional[str] = Header(None),
    settings: Settings = Depends(get_settings),
    db: Session = Depends(get_db),
):
    ensure_admin(settings, authorization)
    row_count = crud.delete_station(db=db, station_id=station_id)
    if row_count:
        return Response(status_code=status.HTTP_204_NO_CONTENT)
    return Response(status_code=status.HTTP_404_NOT_FOUND)
```

In this example, you can see that the endpoint declaration and body are nearly the same as their naïve counterpart, with one important difference: before attempting to delete anything, we call `ensure_admin()`. In the endpoint, we need to grab the authorization header from the request, which is responsible for bearing the token information, so that we can pass it to the `ensure_admin()` function. We do this by declaring it in the function signature, as an optional string that comes from the `Header` object.

The `ensure_admin()` function delegates to the `util.is_admin()` function, which unpacks the token, verifies its validity, and inspects the `role` field within the payload to see if it is that of an admin. If all the checks are successful, it returns `True`, or `False` otherwise. The `ensure_admin()` function does nothing when the check is successful but raises an `HTTPException` with a *403 Forbidden* status code when the check is unsuccessful. This means that if, for any reason, the user is not authorized to make this call, the execution of the endpoint's body will immediately stop and return after its first line.

There are more sophisticated ways to do authentication and authorization, but it would have been impractical to fit them within the chapter. This simple example is good enough as a start to understand how to implement this feature in an API.

Documenting the API

Documenting APIs is a tedious activity. One advantage of using FastAPI is that you do not need to document your project: the documentation is automatically generated by the framework. This is possible thanks to the use of type annotations and Pydantic.

Make sure your API is running, then open a browser and navigate to `http://localhost:8000/docs`. A page will open that should look something like this:

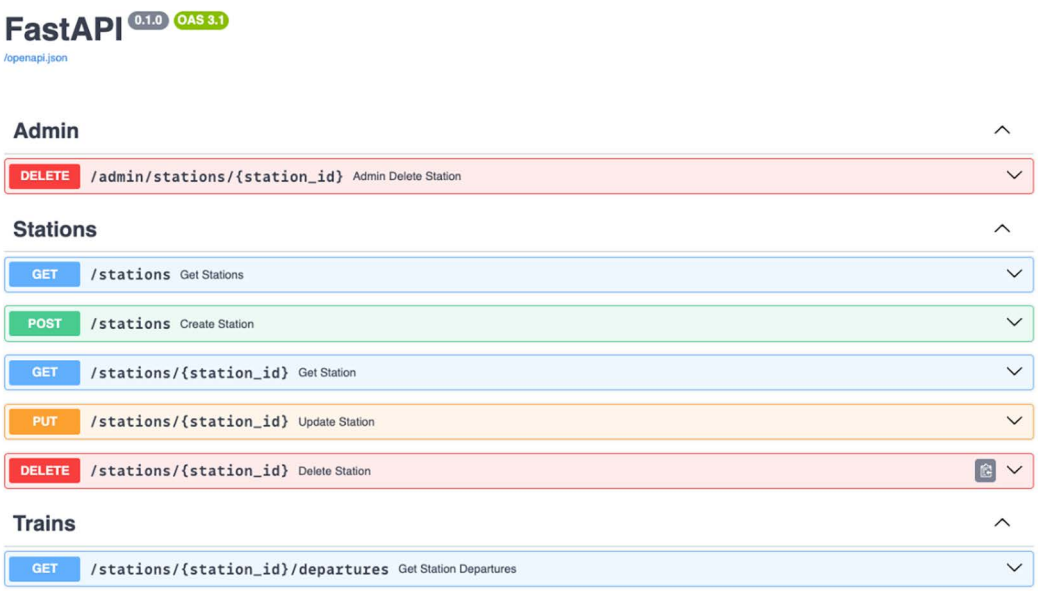


Figure 14.3: A partial screenshot of FastAPI self-generated documentation

In *Figure 14.3*, you can see a list of endpoints. They are categorized using the `tags` argument, which we have specified in each endpoint declaration. This documentation not only allows you to inspect each endpoint in detail but is also interactive, which means you can test the endpoints by making requests directly from the page.

Where do we go from here?

You should now have a basic understanding of API design and main concepts. Of course, studying this chapter's code will deepen your understanding and likely provoke questions. Here are some suggestions if you wish to learn more on the subject:

- Learn FastAPI well. The website offers tutorials both for beginners and advanced programmers. They are quite thorough and cover much more than we could ever include in a single chapter.
- Using the source code from this chapter, enhance the API by adding advanced searching and filtering capabilities. Try implementing a more sophisticated authentication system and exploring the use of background tasks, sorting, and pagination. You could also expand the admin section by adding other endpoints only for admin users.
- Amend the endpoint that books a ticket so that it checks that there are free seats on the train. Each train specifies how many first- and second-class cars there are, as well as the number of seats per car. We designed the train model this way specifically to allow you to practice with this exercise.
- Add tests for the existing endpoints, and for anything else you add to the source code.
- Learn about WSGI (`https://wsgi.readthedocs.io/`) and, if you are familiar with asynchronous programming, ASGI, its asynchronous equivalent (`https://asgi.readthedocs.io/`).
- Learn about middleware in FastAPI, and concepts like **Cross-Origin Resource Sharing (CORS)**, which are important when we run an API in the real world.
- Learn other API frameworks, like Falcon (`https://falcon.readthedocs.io/`), or Django Rest Framework (`https://www.django-rest-framework.org`).
- Learn more about Representational State Transfer (REST). It is used everywhere, but there are different ways to write APIs with it.
- Learn about more advanced API concepts, such as versioning, data formats, protocols, and so on. Learn what headers can do more in-depth.
- Finally, if you are familiar with asynchronous programming, we recommend rewriting the code for this chapter so that it is asynchronous.

Remember to set `DEBUG=true` in the `.env` file, when working with the API, so that you get all the database queries logged automatically in your terminal, and you can check if the SQL code they produce reflects your intentions. This is quite a handy tool to have when SQLAlchemy operations become a bit more complex.

API design is such an important skill. We cannot emphasize enough how essential it is for you to master this subject.

Summary

In this chapter, we explored the world of APIs. We started with a brief overview of the Web and moved on to FastAPI, which leverages type annotations. Those were introduced in *Chapter 12, Introduction to Type Hinting*.

We then discussed APIs in generic terms. We saw different ways to classify them, and the purposes and benefits of their use. We also explored protocols and data-exchange formats.

Finally, we delved into the source code, analyzing a small part of the FastAPI project that we wrote for this chapter.

We concluded the chapter with a series of suggestions for the next steps.

The next chapter discusses developing CLI applications with Python.

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15

CLI Applications

> *A user interface is like a joke. If you have to explain it, it's not that good.*
>
> *– Martin LeBlanc*

In this chapter, we are going to learn how to create **Command-Line Interface** (**CLI**) applications, also known as **Command-Line Applications**, in Python. A CLI is a user interface where users type commands into a console or terminal. Notable examples include the **Bash** and **Zsh** shells on macOS, Linux, and other UNIX-based operating systems, and the Windows **Command Prompt** and **PowerShell**. A CLI application is an application that is primarily used in such a command-line shell environment. One executes a CLI application by typing a command, possibly followed by some arguments, into the shell.

Although **Graphical User Interfaces** (**GUIs**) and web applications are far more popular, CLI applications still have their place. They are especially popular among developers, system administrators, network administrators, and other technical users. There are several reasons for this popularity. Once you are familiar with the required commands, you can often perform a task much faster by typing commands into a CLI than by clicking through menus and buttons in a GUI. Most shells also allow connecting the output of one command directly to the input of another. This is called piping, and it allows users to combine simple commands into data processing pipelines to perform more complex tasks. Sequences of commands can be saved in scripts, allowing for repeatability and automation. It is also easier to document instructions to perform a task by providing exact commands to type, rather than explaining how to navigate a GUI or web interface.

CLI applications are much faster and easier to develop and maintain than graphical or web interfaces. For this reason, development teams sometimes prefer to implement tools for internal use as CLI applications. This allows them to reduce the time and effort spent on building internal tools and focus more on customer-facing features. Learning how to build command-line applications is also an excellent stepping stone toward learning how to build more complex software, such as GUI applications or distributed applications.

In this chapter, we will create a command-line application for interacting with the railway API we studied in the previous chapter. We will use this project to explore the following topics:

- Parsing command-line arguments
- Structuring a CLI application by breaking it down into sub-commands
- Securely dealing with passwords

We will end the chapter with some suggestions for further resources where you can learn more about CLI applications.

Command-line arguments

The primary user interface of a CLI application consists of the arguments that can be passed to it on the command line. Before we start exploring the railway CLI project, let us take a brief look at command-line arguments and the mechanisms Python provides for working with them.

Most applications accept various **options** (or **flags**) as well as **positional arguments**. Some applications consist of several **sub-commands**, each of which has its own distinct set of options and positional arguments.

Positional arguments

Positional arguments represent the main data or objects that the application should operate on. They must be provided in a specific order and are usually not optional. For example, consider the command:

```
$ cp original.txt copy.txt
```

This command will create a copy of the file `original.txt`, named `copy.txt`. Both positional arguments (`original.txt` and `copy.txt`) are required, and changing their order would change the meaning of the command.

Options

Options are used to modify the behavior of an application. They are normally optional and typically consist either of a single letter prefixed with a hyphen or a word prefixed with two hyphens. Options do not need to appear in any particular order or position on the command line. They can even be placed after or between the positional arguments. For example, many applications accept a `-v` or `--verbose` option to enable verbose output. Some options behave like switches, turning some feature on (or off) simply by their presence (or absence). Other options require an additional argument as a value. For example, consider the command:

```
$ grep -r --exclude '*.txt' hello .
```

This will recursively descend into the current directory and search for the string `hello` in all files whose names do not end with `.txt`. The `-r` option causes grep to recursively search a directory. Without this option, it would exit with an error when asked to search a directory instead of a regular file. The `--exclude` option requires a filename pattern (`'*.txt'`) as an argument and causes grep to exclude files matching the pattern from the search.

On Windows, options are traditionally prefixed with a forward-slash character (/) rather than a hyphen. However, many modern and cross-platform applications use hyphens for consistency with other operating systems.

Sub-commands

Complex applications are often divided into several sub-commands. The **Git** revision control system is an excellent example of this. For example, consider the commands

```
$ git commit -m "Fix some bugs"
```

and

```
$ git ls-files -m
```

Here, `commit` and `ls-files` are sub-commands of the `git` application. The `commit` sub-command creates a new commit, using the text passed as an argument to the `-m` option (`"Fix some bugs"`) as the commit message. The `ls-files` command shows information about files in a Git repository. The `-m` option to `ls-files` instructs the command to only show files with modifications that have not been staged for committing.

The use of sub-commands helps to structure and organize the application interface, making it easier for users to find the features they need. Each sub-command can also have its own help messages, which means users can more easily learn how to use a feature without needing to read the full documentation for the entire application. It also promotes the modularity of the code, which improves maintainability and allows adding new commands without modifying existing code.

Argument parsing

Python applications can access the command-line arguments passed to them via `sys.argv`. Let us write a simple script that just prints the value of `sys.argv`:

```
# argument_parsing/argv.py
import sys

print(sys.argv)
```

When we run this without passing any arguments, the output looks as follows:

```
$ python argument_parsing/argv.py
['argument_parsing/argv.py']
```

If we pass some arguments, we get the following:

```
$ python argument_parsing/argv.py your lucky number is 13
['argument_parsing/argv.py', 'your', 'lucky', 'number', 'is', '13']
```

As you can see, `sys.argv` is a list of strings. The first element is the command used to run the application. The remaining elements contain the command-line arguments.

Simple applications that do not accept any options can simply extract positional arguments directly from `sys.argv`. For applications that do take options, however, the argument parsing logic can get complicated. Fortunately, the `argparse` module in the Python standard library provides a command-line argument parser that makes it easy to parse arguments without needing to write any complicated logic.

There are several third-party library alternatives to `argparse`. We will not cover any of these in this chapter, but we will provide some links for a few of the most popular ones at the end.

For example, we have written a script that takes `name` and `age` as positional arguments and prints out a greeting. Given the name `Heinrich` and age `42`, it should print `"Hi Heinrich. You are 42 years old."` It accepts a custom greeting to use instead of `"Hi"`, via the `-g` option. Adding `-r` or `--reverse` to the command line results in reversing the message before printing.

```
# argument_parsing/greet.argparse.py
import argparse

def main():
    args = parse_arguments()
    print(args)

    msg = "{greet} {name}. You are {age} years old.".format(
        **vars(args)
    )
    if args.reverse:
        msg = msg[::-1]

    print(msg)

def parse_arguments():
    parser = argparse.ArgumentParser()
    parser.add_argument("name", help="Your name")
    parser.add_argument("age", type=int, help="Age")
    parser.add_argument("-r", "--reverse", action="store_true")
    parser.add_argument(
        "-g", default="Hi", help="Custom greeting", dest="greet"
    )
    return parser.parse_args()

if __name__ == "__main__":
    main()
```

Let us take a closer look at the `parse_arguments()` function. We start by creating an instance of the `ArgumentParser` class. Then, we proceed to define the arguments we accept by calling the `add_argument()` method. We start with the `name` and `age` positional arguments, providing help strings for each and specifying that `age` must be an integer. If no `type` is specified, the arguments will be parsed as strings. The next argument is an option, which can be specified on the command line as either `-r` or `--reverse`. The last argument is the `"-g"` option, with the default value `"Hi"`. Finally, we call the `parse_args()` method of the parser, to parse the command-line arguments. This will return a `Namespace` object containing the argument values parsed from the command line.

The `action` keyword argument to `add_argument()` defines how the parser should process the corresponding command-line argument. The default action, if none is specified, is `"store"`, which stores the value provided on the command line as an attribute on the object returned when parsing the arguments. The `"store_true"` action means that the option will be treated as a switch. If it is present on the command line, the parser will store the value `True`; if it is absent, we get `False`. The `dest` keyword argument specifies the name of the attribute in which the value will be stored. If `dest` is not specified, the parser defaults to using the name of a positional argument, or the first long option string for option arguments (with the leading `--` removed). If only a short option string is provided, that is used (with the `-` removed).

Let us see what happens when we run this script.

```
$ python argument_parsing/greet.argparse.py Heinrich -r 42
Namespace(name='Heinrich', age=42, reverse=True, greet='Hi')
.dlo sraey 24 era uoY .hcirnieH iH
```

If we provide incorrect arguments, we get a `usage` message indicating what the expected arguments are, as well as an error message telling us what we did wrong:

```
$ python argument_parsing/greet.argparse.py -g -r Heinrich 42
usage: greet.argparse.py [-h] [-r] [-g GREET] name age
greet.argparse.py: error: argument -g: expected one argument
```

The `usage` message mentions a `-h` option, which we did not add. Let us see what it does:

```
$ python argument_parsing/greet.argparse.py -h
usage: greet.argparse.py [-h] [-r] [-g GREET] name age

positional arguments:
  name           Your name
  age            Age
```

```
options:
  -h, --help     show this help message and exit
  -r, --reverse
  -g GREET       Custom greeting
```

The parser automatically adds a `help` option, which shows detailed usage information, including the `help` strings we passed to the `add_argument()` method.

To help you appreciate the power of `argparse`, we have added a version of the greeter script that does not use `argparse` in the source code for this chapter. You can find it in the `argument_parsing/greet.argv.py` file.

We have only scratched the surface of what `argparse` is capable of in this section. We will show you a few more advanced features in the next section, as we explore the railway CLI application.

Building a CLI client for the railway API

Now that we have covered the basics of command-line argument parsing, we are ready to start working on a more complex CLI application. You will find the code for the application under the project directory in the source code for this chapter. Let us start by taking a look at the contents of the `project` directory.

```
$ tree -a project
project
├── .env.example
├── railway_cli
│   ├── __init__.py
│   ├── __main__.py
│   ├── api
│   │   ├── __init__.py
│   │   ├── client.py
│   │   └── schemas.py
│   ├── cli.py
│   ├── commands
│   │   ├── __init__.py
│   │   ├── admin.py
│   │   ├── base.py
│   │   └── stations.py
```

```
│   ├── config.py
│   └── exceptions.py
└── secrets
    ├── railway_api_email
    └── railway_api_password
```

The `.env.example` file is a template for creating a `.env` configuration file for the railway application. The files in the `secrets` directory contain credentials needed to authenticate with the railway API as an admin user.

To successfully run the examples in this section, you need to have the API from *Chapter 14, Introduction to API Development*, running. You also need to create a copy of the `.env.example` file named `.env` and ensure it contains the correct URL for the API.

The `railway_cli` directory is the Python package for the railway CLI application. The `api` sub-package contains the code for interacting with the railway API. In the `commands` sub-package, you will find the implementation of the sub-commands of the application. The `exceptions.py` module defines exceptions for errors that can occur within the application. `config.py` contains code for handling global configuration settings. The main function driving the CLI application is in `cli.py`. The `__main__.py` module is a special file that makes the package executable. When the package is executed with a command like

```
$ python -m railway_cli
```

Python will load and execute the `__main__.py` module. Its contents are as follows:

```
# project/railway_cli/__main__.py
from . import cli

cli.main()
```

All this module does is import the `cli` module and call the `cli.main()` function, which is the main entry point for the CLI application.

Interacting with the railway API

Before we delve into the command-line interface code, we want to briefly discuss the API client code. Instead of looking at the code in detail, we will just give you a high-level overview. We leave it as an exercise for you to study the code in depth.

In the `api` sub-package, you will find two modules, `client.py` and `schemas.py`:

- `schemas.py` defines `pydantic` models to represent the objects we expect to receive from the API (we have only defined models for stations and trains).
- `client.py` contains three classes and some helper functions:
    - `HTTPClient` is a generic class for making **HTTP** requests. It is a wrapper around a `Session` object from the `requests` library. It has methods corresponding to the HTTP verbs the API uses (`get`, `post`, `put`, and `delete`). This class takes care of error handling and extracting data from API responses.
    - `StationClient` is a higher-level client for interacting with the API's station endpoints.
    - `AdminClient` is a higher-level client for working with the admin endpoints. It has a method for authenticating users with the `users/authenticate` endpoint and a method for deleting a station via the `admin/stations/{station_id}` endpoint.

Creating the command-line interface

We will start our exploration of the code with the `cli.py` module. We will examine it in chunks, starting with the `main()` function.

```
# project/railway_cli/cli.py
import argparse
import sys

from . import __version__, commands, config, exceptions
from .commands.base import Command

def main(cmdline: list[str] | None = None) -> None:
    arg_parser = get_arg_parser()
    args = arg_parser.parse_args(cmdline)

    try:
        # args.command is expected to be a Command class
        command: Command = args.command(args)
        command.execute()
    except exceptions.APIError as exc:
        sys.exit(f"API error: {exc}")
    except exceptions.CommandError as exc:
```

```
        sys.exit(f"Command error: {exc}")
    except exceptions.ConfigurationError as exc:
        sys.exit(f"Configuration error: {exc}")
```

We start by importing the standard library modules `argparse` and `sys`. We also import `__version__`, `config`, `commands`, and `exceptions` from the current package and the `Command` class from the `commands.base` module.

It is a common convention for Python modules and packages to expose their version number under the name `__version__`. It is typically a string and is normally defined in the top-level `__init__.py` file of a package.

In the `main()` function, we call `get_arg_parser()` to get an `ArgumentParser` instance and call its `parse_args()` method to parse the command-line arguments. We expect the returned `Namespace` object to have a `command` attribute, which should be a `Command` class. We create an instance of this class, passing it the parsed arguments. Finally, we call the command's `execute()` method.

We handle `APIError`, `CommandError`, and `ConfigurationError` exceptions by calling `sys.exit()` to exit with an error message tailored to the type of exception that occurred. These are the only exceptions raised in our application code. If any other unexpected error happens, Python will terminate the application and print a full exception traceback to the user's console. This may not seem very user-friendly, but it will make debugging much easier. Users of CLI applications also tend to be more technically adept and so are less likely to be put off by exception tracebacks than users of GUI or web applications.

Note that the `main()` function has an optional parameter `cmdline`, which we pass to the `parse_args()` method. If `cmdline` is `None`, `parse_args()` will default to parsing arguments from `sys.argv`. However, if we pass a list of strings, `parse_args()` will parse that instead. Structuring the code like this is especially useful for unit testing as it allows us to avoid manipulating the global `sys.argv` in our tests.

We will look at the `Command` class and how the argument parser is set up to return the `Command` class to execute shortly. Let us first turn our attention to the `get_arg_parser()` function, though.

```
# project/railway_cli/cli.py
def get_arg_parser() -> argparse.ArgumentParser:
    parser = argparse.ArgumentParser(
        prog=__package__,
```

```
        description="Commandline interface for the Railway API",
        formatter_class=argparse.ArgumentDefaultsHelpFormatter,
    )
    parser.add_argument(
        "-V",
        "--version",
        action="version",
        version=f"%(prog)s {__version__}",
    )
    config.configure_arg_parser(parser)
    commands.configure_parsers(parser)
    return parser
```

The `get_arg_parser()` function creates and configures an `ArgumentParser` instance for the application. The `prog` argument specifies the program name to use in help messages. Normally, `argparse` takes this from `sys.argv[0]`; however, for a package executed via `python -m package_name`, that is `__main__.py`, so we override it with the name of the package instead. The `description` argument provides a brief description of the program to display in the help message. The `formatter_class` determines how help messages are formatted (`ArgumentDefaultsHelpFormatter` adds the default values of all options to the help message). We add a `"-V"` or `"--version"` option using the `"version"` action, which will print the `version` message and exit if this option is encountered on the command line. Finally, we call the `config.configure_arg_parser()` and `commands.configure_parsers()` functions to further configure the parser before returning it.

The Python import system sets the `__package__` attribute of every imported module to the name of the package it belongs to.

In the next sections, we will look at the command-line argument configuration for the `config` and `commands` modules, starting with `config`.

Configuration files and secrets

Besides command-line arguments, many CLI applications also read settings from configuration files. Configuration files are often used for settings like API URLs that do not usually change from one invocation of an application to the next. It would be rather tedious for users to provide these on the command line every time they run an application.

Another common use case for configuration files is to supply passwords and other secrets. It is not considered good security practice to provide passwords as command-line arguments because, on most operating systems, any logged-in user can see the full command line of any running application. Most shells also have a command history feature, which can potentially expose passwords that are passed as command-line arguments. It is much more secure to provide passwords in configuration files or dedicated secret files, which are files used to configure a secret, such as a password. The filename corresponds to the name of the secret and the content of the file is the secret itself.

It is very important to remember that it is never safe to store secrets alongside our code. Especially if you use a versioning system, like Git or Mercurial, be careful never to commit any secret with the source code.

In the `railway_cli` application, the `config` module is responsible for handling configuration files and secrets. We use the `pydantic-settings` library, which we already encountered in *Chapter 14, Introduction to API Development*, to manage the configuration. Let us look at the code in chunks.

```
# project/railway_cli/config.py
import argparse
from getpass import getpass

from pydantic import EmailStr, Field, SecretStr, ValidationError
from pydantic_settings import BaseSettings, SettingsConfigDict

from .exceptions import ConfigurationError

class Settings(BaseSettings):
    url: str
    secrets_dir: str | None = None

class AdminCredentials(BaseSettings):
    model_config = SettingsConfigDict(env_prefix="railway_api_")
    email: EmailStr
    password: SecretStr = Field(
        default_factory=lambda: SecretStr(
            getpass(prompt="Admin Password: ")
        )
    )
```

After the imports at the top of the file, we have two classes: `Settings` and `AdminCredentials`. Both inherit from `pydantic_settings.BaseSettings`. The `Settings` class defines the general configuration for the `railway_cli` application:

- `url`: is used to configure the railway API URL.
- `secrets_dir`: can be used to configure a path to a directory containing secret files. The API admin credentials will be loaded from secret files in this directory.

The `AdminCredentials` class defines the credentials needed to authenticate with the API as an admin user. The `env_prefix` argument to the `SettingsConfigDict` will be prefixed to the field names when looking up values in the secrets directory. For example, the `password` will be looked up in a file named `railway_api_password`. The `AdminCredentials` class contains the following fields:

- `email`: will contain the admin email address to authenticate with. We use the `pydantic.EmailStr` type to ensure that it contains a valid email address.
- `password`: will contain the admin password. We use the `pydantic.SecretStr` type to ensure that the value will be masked with asterisks when printed (for example, in application logs). If no value is provided when the class is instantiated (via a secret file or an argument to the class constructor), `pydantic` will call the function provided via the `default_factory` argument to the `Field` function. We use this to call the standard library `getpass` function to securely prompt the user for the admin password.

Below these class definitions, you will find the `configure_arg_parser()` function. Let us look at that now:

```
# project/railway_cli/config.py
def configure_arg_parser(parser: argparse.ArgumentParser) -> None:
    config_group = parser.add_argument_group(
        "configuration",
        description="""The API URL must be set in the
        configuration file. The admin email and password should be
        configured via secrets files named email and password in a
        secrets directory.""",
    )
    config_group.add_argument(
        "--config-file",
        help="Load configuration from a file",
        default=".env",
    )
```

```
    config_group.add_argument(
        "--secrets-dir",
        help="""The secrets directory. Can also be set via the
        configuration file.""",
    )
```

We use the argument parser's `add_argument_group()` method to create an argument group named `"configuration"` and give it a `description`. We add options allowing a user to specify a configuration file name and a secrets directory to this group. Note that argument groups do not affect how arguments are parsed or returned. It only means that these arguments will be grouped together under a common heading in the help message.

For the sake of simplicity, we set the default configuration file path in this example to `.env`. It is, however, considered best practice to use the standard configuration file locations for the platform your application is running on. The `platformdirs` library (`https://platformdirs.readthedocs.io`) can be particularly helpful for this.

The final part of the `config.py` module consists of helper functions for retrieving the settings and admin credentials:

```
# project/railway_cli/config.py
def get_settings(args: argparse.Namespace) -> Settings:
    try:
        return Settings(_env_file=args.config_file)
    except ValidationError as exc:
        raise ConfigurationError(str(exc)) from exc

def get_admin_credentials(
    args: argparse.Namespace, settings: Settings
) -> AdminCredentials:
    secrets_dir = args.secrets_dir
    if secrets_dir is None:
        secrets_dir = settings.secrets_dir

    try:
        return AdminCredentials(_secrets_dir=secrets_dir)
    except ValidationError as exc:
        raise ConfigurationError(str(exc)) from exc
```

The `get_settings()` function creates and returns an instance of the `Settings` class. The `_env_file=args.config_file` argument tells `pydantic-settings` to load the settings from the file specified via the `--config-file` command-line option (which defaults to `.env`). The `get_admin_credentials()` function creates and returns an instance of the `AdminCredentials` class. The `_secrets_dir` argument to the class specifies the secrets directory where `pydantic-settings` will look for the credentials. If a `--secrets-dir` option was set on the command line, we will use that; otherwise, use `settings.secrets_dir`. If that is also `None`, no secrets directory will be used.

Creating sub-commands

The railway API has separate endpoints for listing stations, creating stations, getting departures, and so on. It makes sense to have a similar structure in our application. There are many ways of structuring the code for sub-commands. In this application, we have chosen to use an object-oriented approach. Each command is implemented as a class, with a method to configure the argument parser with the options and arguments it needs, and a method to execute the command. All commands are subclasses of the `Command` base class. You will find it in the `commands/base.py` module:

```
# project/railway_cli/commands/base.py
import argparse
from typing import ClassVar

from ..api.client import HTTPClient
from ..config import get_settings

class Command:
    name: ClassVar[str]
    help: ClassVar[str]

    def __init__(self, args: argparse.Namespace) -> None:
        self.args = args
        self.settings = get_settings(args)
        self.api_client = HTTPClient(self.settings.url)

    @classmethod
    def configure_arg_parser(
        cls, parser: argparse.ArgumentParser
    ) -> None:
```

```
            raise NotImplementedError

        def execute(self) -> None:
            raise NotImplementedError
```

As you can see, the `Command` class is an ordinary class. The `ClassVar` annotation on `name` and `help` indicates that these are expected to be class attributes, rather than instance attributes. The `__init__()` method takes an `argparse.Namespace` object, which it assigns to `self.args`. It calls `get_settings()` to load the configuration file. Before returning, it also creates an `HTTPClient` object (from `api/client.py`) and assigns it to `self.api_client`.

The `configure_arg_parser()` class method and `execute()` method both raise `NotImplementedError` when called, which means that subclasses need to override these methods with their own implementations.

To set up argument parsing for the sub-commands, we need to create a parser for each sub-command and configure it by calling the `configure_arg_parser()` class method of the `Command` class. The `commands.configure_parsers()` function is responsible for this process. Let us take a look at that now.

```
# project/railway_cli/commands/__init__.py
import argparse

from .admin import admin_commands
from .base import Command
from .stations import station_commands

def configure_parsers(parser: argparse.ArgumentParser) -> None:
    subparsers = parser.add_subparsers(
        description="Available commands", required=True
    )
    command: type[Command]
    for command in [*admin_commands, *station_commands]:
        command_parser = subparsers.add_parser(
            command.name, help=command.help
        )
        command.configure_arg_parser(command_parser)
        command_parser.set_defaults(command=command)
```

The `parser.add_subparsers()` method returns an object that can be used to attach sub-command parsers to the main parser. The `description` argument is used to generate the help text for the sub-commands, and `required=True` ensures that the parser will produce an error if a sub-command is not supplied on the command line.

We iterate over the list of `admin_commands` and `station_commands` and create a sub-parser for each of them. The `add_parser()` method expects the `name` of the sub-command and any arguments that can be passed to the `ArgumentParser` class. It returns a new `ArgumentParser` instance, which we pass to the `command.configure_arg_parser()` class method. Note that the `command: type[Command]` type annotation indicates that we expect all elements of `admin_commands` and `station_commands` to be subclasses of `Command`.

The `set_defaults()` method allows us to set attributes on the namespace returned by the parser, independently of what is on the command line. We use this to set the `command` attribute for each sub-parser to the corresponding `Command` subclass. The `Namespace` object returned by the `parse_args()` method will only contain attributes from exactly one sub-parser (the one corresponding to the sub-command provided on the command line). Thus, when we call `args.command(args=args)` in the `cli.main()` function, we are guaranteed to get an instance of the command class for the command selected by the user.

Now that we have put together all the code to configure the argument parser, we can look at the help text that is generated when we run the application with the `-h` option.

```
$ python -m railway_cli -h
usage: railway_cli [-h] [-V] [--config-file CONFIG_FILE]
                   [--secrets-dir SECRETS_DIR]
                   {admin-delete-station,get-station,...}
                   ...
Commandline interface for the Railway API
options:
  -h, --help            show this help message and exit
  -V, --version         show program's version number and exit
configuration:
  The API URL must be set in the configuration file. ...
  --config-file CONFIG_FILE
                        Load configuration from a file (default:
                        .env)
  --secrets-dir SECRETS_DIR
                        The secrets directory. Can also be set
```

```
                        via the configuration file. (default:
                        None)
subcommands:
  Available commands
  {admin-delete-station,get-station,list-stations,...}
    admin-delete-station
                        Delete a station
    get-station         Get a station
    list-stations       List stations
    create-station      Create a station
    update-station      Update an existing station
    get-arrivals        Get arrivals for a station
    get-departures      Get departures for a station
```

We have trimmed some of the output and removed blank lines, but you can see that there is a `usage` summary showing how to use the command, followed by the `description` we set when creating the argument parser. This is followed by the global `options` section with the `-h` or `--help` option and the `-V` or `--version` option. Next, we get a `configuration` section with the description and options we configured in the `config.configure_arg_parser()` function. Finally, we have a `subcommands` section, with the description we passed to the argument parser's `add_subparsers()` method in `commands.configure_parsers()` and a list of all the available sub-commands with the help string we set for each of them.

We have seen the base class for sub-commands and the code to configure the argument parser to work with sub-commands. Let us now look at the implementation of a sub-command.

Implementing sub-commands

The sub-command parsers are completely independent, so we can implement sub-commands without any risk that their command-line options might conflict with one another. We only need to ensure that the command names are unique. This means we can extend the application by adding commands without needing to modify any existing code. The class-based approach we have chosen for this application makes it easy to add commands. We just have to create a new `Command` subclass, define its `name` and `help` text, and implement the `configure_arg_parser()` and `execute()` methods. As an example, let us look at the code for the `create-station` command.

```
# project/railway_cli/commands/stations.py
class CreateStation(Command):
    name = "create-station"
```

```
    help = "Create a station"

    @classmethod
    def configure_arg_parser(
        cls, parser: argparse.ArgumentParser
    ) -> None:
        parser.add_argument(
            "--code", help="The station code", required=True
        )
        parser.add_argument(
            "--country", help="The station country", required=True
        )
        parser.add_argument(
            "--city", help="The station city", required=True
        )

    def execute(self) -> None:
        station_client = StationClient(self.api_client)
        station = station_client.create(
            code=self.args.code,
            country=self.args.country,
            city=self.args.city,
        )
        print(station)
```

Note that we have not reproduced the imports from the top of the `commands/stations.py` module here. As you can see, the code for the command is quite straightforward. The `configure_arg_parser()` class method adds options for the station code, city, and country.

Note that all three are marked as `required`. The Python `argparse` documentation discourages the use of `required` options; however, in some circumstances, it can lead to a more user-friendly interface. If a command requires more than two arguments with different meanings, it can become difficult for users to remember the correct order. Using options instead means that the order does not matter, and it is immediately obvious what each of the arguments means.

Let us see what happens when we run this command. First, with the `-h` option to see the help message:

```
$ python -m railway_cli create-station -h
usage: railway_cli create-station [-h] --code CODE --country
                                  COUNTRY --city CITY

options:
  -h, --help         show this help message and exit
  --code CODE        The station code
  --country COUNTRY  The station country
  --city CITY        The station city
```

The help message clearly shows how to use the command. Now we can create a station:

```
$ python -m railway_cli create-station --code LSB --city Lisbon \
    --country Portugal
id=12 code='LSB' country='Portugal' city='Lisbon'
```

The output shows that the station was created successfully and assigned the `id` `12`.

This brings us to the end of our exploration of the railway CLI application.

Other resources and tools

We will finish this chapter with some links to resources where you can learn more and some useful libraries for developing CLI applications:

- Although we have tried to make this chapter as comprehensive as we could, the `argparse` module has many more features than we could showcase here. The official documentation at `https://docs.python.org/3/library/argparse.html` is excellent, though.
- If `argparse` is not to your liking, there are several third-party libraries available for command-line argument parsing. We suggest that you try them all:
    - **Click** is by far the most popular third-party CLI library for Python. Besides command-line parsing, it also provides features for creating interactive applications (such as input prompts) and for producing colorful output. You can learn about it at `https://click.palletsprojects.com`.
    - **Typer** was created by the same developers as FastAPI. It aims to apply the same principles FastAPI applies to API development to CLI development. You can read about it at `https://typer.tiangolo.com/`.

- **Pydantic Settings**, which we used for configuration management in this chapter and in *Chapter 14, Introduction to API development*, also supports parsing command-line arguments. See `https://docs.pydantic.dev/latest/concepts/pydantic_settings/#command-line-support` to learn more about this.
- Most modern shells support programmable command-line tab completion. Providing command-line completion can make your CLI application much easier to use. The `argcomplete` library (`https://kislyuk.github.io/argcomplete/`) provides command-line completion in the `bash` and `zsh` shells for applications that use `argparse` to handle command-line arguments.
- The *Command Line Interface Guidelines* (`https://clig.dev/`) is a comprehensive open-source resource with excellent advice for designing user-friendly command-line interfaces.

Summary

In this chapter, we learned about command-line applications by developing a CLI client for the railway API that we created in *Chapter 14, Introduction to API Development*. We learned how to parse command-line arguments with the standard library `argparse` module. We looked at how to structure a CLI application interface by using sub-commands and saw how this can help us build modular applications that are easy to maintain and extend. We concluded the chapter with some links to other libraries for CLI application development in Python and some resources where you can learn more.

Working with command-line applications is an excellent way to practice the skills you learned throughout this book. We encourage you to study the code for this chapter, extend it by adding more commands, and improve it by adding logging and tests.

In the next chapter, we will learn how to package and publish Python applications.

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`https://discord.com/invite/uaKmaz7FEC`

16

Packaging Python Applications

> *"Do you have any cheese at all?" "No."*
>
> *– Monty Python, the "Cheese Shop" sketch*

In this chapter, we are going to learn how to create an installable package for a Python project and publish it for others to use.

There are many reasons why you should publish your code. In *Chapter 1, A Gentle Introduction to Python*, we said that one of the benefits of Python is the vast ecosystem of third-party packages that you can install for free using `pip`. Most of these were created by developers just like you and, by contributing with your own projects, you will be helping to ensure that the community keeps thriving. In the long term, it will also help to improve your code, since exposing it to more users means bugs might be discovered sooner. Finally, if you are trying to get a job as a software developer, it really helps to be able to point to projects that you have worked on.

The best way to learn about packaging is to go through the process of creating a package and publishing it. That is what we are going to do in this chapter. The project that we will be working with is the Railway **command-line interface (CLI)** application we developed in *Chapter 15, CLI Applications*.

In this chapter, we are going to learn about the following:

- How to create a distribution package for your project
- How to publish your package
- The different tools for packaging

Before we start packaging and publishing our project, we will give you a brief introduction to the **Python Package Index** (**PyPI**) and some important terminology around Python packaging.

The Python Package Index

PyPI is an online repository of Python packages, hosted at `https://pypi.org`. It has a web interface that can be used to browse or search for packages and view their details. It also has APIs for tools like `pip` to find and download packages to install. PyPI is open for anybody to register and distribute their projects for free. Anybody can also install any package from PyPI for free.

The repository is organized into **projects**, **releases**, and **distribution packages**. A project is a library, script, or application with its associated data or resources. For example, *FastAPI*, *Requests*, *pandas*, *SQLAlchemy*, and our Railway CLI application are all projects. `pip` itself is a project as well. A release is a particular version (or snapshot in time) of a project. Releases are identified by version numbers. For example, `pip` *24.2* is a release of the `pip` project. Releases are distributed in the form of distribution packages. These are archive files, tagged with the release version, which contain the Python modules, data files, and so on, that make up the release. Distribution packages also contain metadata about the project and release, such as the name of the project, the authors, the release version, and dependencies that also need to be installed. Distribution packages are also referred to as **distributions** or just **packages**.

In Python, the word **package** is also used to refer to an importable module that can contain other modules, usually in the form of a folder containing a `__init__.py` file. It is important not to confuse this type of importable package with a distribution package. In this chapter, we will mostly use the term package to refer to a distribution package. Where there is ambiguity, we will use the terms **importable package** or **distribution package**.

Distribution packages can be either **source distributions** (also known as **sdists**), which require a build step before they can be installed, or **built distributions**, which only require the archive contents to be moved to the correct locations during installation. The current format of source distributions was originally defined by PEP 517. The formal specification can be found at `https://packaging.python.org/specifications/source-distribution-format/`. The standard built distribution format is called a **wheel** and was originally defined in PEP 427. The current version of the wheel specification can be found at `https://packaging.python.org/specifications/binary-distribution-format/`. The wheel format replaced the (now deprecated) **egg** built distribution format.

PyPI was initially nicknamed the Cheese Shop, after the famous Monty Python sketch that we quoted at the beginning of the chapter. Thus, the wheel distribution format is not named after the wheels of a car, but after wheels of cheese.

To help understand all of this, let us go through a quick example of what happens when we run `pip install`. We will use `pip` to install release *2.32.3* of the *requests* project. To allow us to see exactly what `pip` is doing, we will use the `-v` command line option three times, to make the output as verbose as possible. We will also add the `--no-cache` command-line option to force `pip` to download packages from PyPI and not use any locally cached packages it might have. The output looks something like this (note that we have trimmed the output to fit on the page and omitted several lines; you can find the complete output in the source code for this chapter in the file `pip_install.txt`):

```
$ pip install -vvv --no-cache requests==2.32.3
Using pip 24.2 from ... (python 3.12)
...
1 location(s) to search for versions of requests:
* https://pypi.org/simple/requests/
```

`Pip` tells us that it has found information about the `requests` project at `https://pypi.org/simple/requests/`. The output continues with a list of all the available distributions of the `requests` project:

```
  Found link https://.../requests-0.2.0.tar.gz..., version: 0.2.0
  ...
  Found link https://.../requests-2.32.3-py3-none-any.whl...
    (requires-python:>=3.8), version: 2.32.3
  Found link https://.../requests-2.32.3.tar.gz...
    (requires-python:>=3.8), version: 2.32.3
```

Now, `pip` collects the distribution for the release we requested. It downloads the metadata for the wheel distribution:

```
Collecting requests==2.32.3
  ...
  Downloading requests-2.32.3-py3-none-any.whl.metadata (4.6 kB)
```

Next, `pip` extracts the list of dependencies from the package metadata and proceeds to find and collect their metadata in the same way. Once all the required packages have been found, they can be downloaded and installed:

```
Downloading requests-2.32.3-py3-none-any.whl (64 kB)
...
Installing collected packages: urllib3, ..., certifi, requests
...
Successfully installed ... requests-2.32.3 ...
```

If `pip` had downloaded a source distribution for any of the packages (which might happen if no suitable wheel is available), it would have needed to build the package before installing it.

Now that we know the difference between a project, a release, and a package, we can start working on preparing a release and building distribution packages for the Railway CLI application.

Packaging with Setuptools

We will be using the **Setuptools** library to package our project. Setuptools is the oldest actively developed packaging tool for Python, and still the most popular. It is an extension of the original, standard library `distutils` packaging system. The `distutils` module was deprecated in Python 3.10 and removed from the standard library in Python 3.12.

In this section, we will be looking at how to set up our project to build packages with Setuptools.

Project layout

There are two popular conventions for laying out files in a Python project:

- In the **src layout,** the importable packages that need to be distributed are placed in a folder named `src` within the main project folder.
- In the **flat layout,** the importable packages are placed directly in the top-level project folder.

The src layout has the advantage of being explicit about which files will be included in the distribution. This reduces the likelihood of accidentally including other files, such as scripts that are only meant for use during development. The src layout can, however, be less convenient during development as it is not possible to import the package from a script or Python console running in the top-level project folder without first installing the distribution in a virtual environment.

Proponents of the src layout argue that being forced to install the distribution package during development is actually a benefit, as it increases the likelihood that mistakes in creating the distribution package will be discovered during development.

For this project, we have chosen to use the src layout:

```
$ tree -a railway-project
railway-project
├── .flake8
├── CHANGELOG.md
├── LICENSE
├── README.md
├── pyproject.toml
├── src
│   └── railway_cli
│       ├── __init__.py
│       └── ...
└── test
    ├── __init__.py
    └── test_get_station.py
```

The `src/railway_cli` folder contains the code for the `railway_cli` importable package. We also added some tests, as an example for you to expand on, in the `test` folder. The `.flake8` file contains configuration for `flake8`, a Python code style checker that can help to point out PEP 8 violations in our code.

We will describe each of the remaining files in more detail below. Before that, though, let us look at how to install the project in a virtual environment during development.

Development installation

The most common approach to working with an src layout is to use a **development installation**, also known as **development mode**, or an **editable installation**. This will build and install a wheel for the project. However, instead of copying the code into the virtual environment, it will add a link in the virtual environment to the source code in your project folder. This allows you to import and run the code as if it is installed, but any changes you make to the code will take effect without needing to rebuild and reinstall.

Let us try this now. Open a console, go to the source code folder for this chapter, create a new virtual environment, activate it, and run the following command:

```
$ pip install -e railway-project
Obtaining file:///.../ch16/railway-project
  Installing build dependencies ... done
```

```
  Checking if build backend supports build_editable ... done
  Getting requirements to build editable ... done
  Preparing editable metadata (pyproject.toml) ... done
...
Building wheels for collected packages: railway-cli
  Building editable for railway-cli (pyproject.toml) ... done
  Created wheel for railway-cli: filename=...
  ...
Successfully built railway-cli
Installing collected packages: ... railway-cli
Successfully installed ... railway-cli-0.0.1 ...
```

As the output shows, when we run `pip install` with the `-e` (or `--editable`) option and give it the path to a project folder, it builds an editable wheel and installs it in the virtual environment.

Now, if you run:

```
$ python -m railway_cli
```

It should work as it did in the previous chapter. You can verify that we really have an editable installation by changing something in the code (for example, add a `print()` statement) and running it again.

Now that we have a working editable installation of the project, let us discuss each of the files in the project folder in more detail.

Changelog

Although it is not required, it is considered good practice to include a change log file with your project. This file summarizes the changes made in each release of your project. The change log is useful for informing your users of new features that are available or of changes in the behavior of your software that they need to be aware of.

Our changelog file is named `CHANGELOG.md` and is written in **Markdown** format.

License

You should include a license that defines the terms under which your code is distributed. There are many software licenses that you can use. If you are not sure which to choose, the website `https://choosealicense.com/` is a useful resource that can help you. However, if you are at all in doubt about the legal implications, or need advice, you should consult a legal professional.

We are distributing our Railway CLI project under the MIT License. This is a simple license that allows anyone to use, distribute, or modify the code as long as they include our original copyright notice and license.

By convention, the license is included in a text file named `LICENSE` or `LICENSE.txt`, although some projects also use other names, such as `COPYING`.

README

Your project should also include a *README* file describing the project, why it exists, and even some basic usage instructions. The file can be in plain text format or use a markup syntax like **reStructuredText** or **Markdown**. The file is typically called `README` or `README.txt` if it is a plain text file, `README.rst` for reStructuredText, or `README.md` for Markdown.

Our `README.md` file contains a short paragraph describing the purpose of the project and some simple usage instructions.

Markdown and reStructuredText are widely used markup languages that are designed to be easy to read or write in raw form but can also easily be converted to HTML to create simple web pages. You can read more about them at `https://daringfireball.net/projects/markdown/` and `https://docutils.sourceforge.io/rst.html`.

pyproject.toml

This file was introduced by PEP 518 (`https://peps.python.org/pep-0518/`) and extended by PEP 517 (`https://peps.python.org/pep-0517/`). The aim of these PEPs was to define standards to allow projects to specify their build dependencies and to specify what build tool should be used to build their packages. For a project using Setuptools, this looks like:

```
# railway-project/pyproject.toml
[build-system]
requires = ["setuptools>=66.1.0", "wheel"]
build-backend = "setuptools.build_meta"
```

Here, we have specified that we require at least version 66.1.0 of Setuptools (this is the oldest version that is compatible with Python 3.12) and any release of the `wheel` project, which is the reference implementation of the wheel distribution format. Note that the `requires` field here does not list dependencies for running our code, only for building a distribution package. We will talk about how to specify dependencies for running our project later in this chapter.

The `build-backend` field specifies the Python object that will be used to build packages. For Setuptools, this is the `build_meta` module in the `setuptools` (importable) package.

PEP 518 also allows you to put configurations for other development tools in the `pyproject.toml` file. Of course, the tools in question also need to support reading their configuration from this file:

```
# railway-project/pyproject.toml
[tool.black]
line-length = 66

[tool.isort]
profile = 'black'
line_length = 66
```

We have added configuration for *black*, a popular code formatting tool, and *isort*, a tool for sorting imports alphabetically, to our `pyproject.toml` file. We have configured both tools to use a line length of 66 characters to ensure our code will fit on a book page. We have also configured `isort` to maintain compatibility with `black`.

You can learn more about `black` and `isort` on their websites at `https://black.readthedocs.io/` and `https://pycqa.github.io/isort`.

PEP 621 (`https://peps.python.org/pep-0621/`) introduced the ability to specify all project metadata in the `pyproject.toml` file. This has been supported in Setuptools since version 61.0.0. We will take a closer look at this in the next section.

Package metadata

The project metadata is defined in the `project` table in the `pyproject.toml` file. Let us go through it a few entries at a time:

```
# railway-project/pyproject.toml
[project]
name = "railway-cli"
authors = [
  {name="Heinrich Kruger", email="heinrich@example.com"},
  {name="Fabrizio Romano", email="fabrizio@example.com"},
]
```

The table starts with the `[project]` heading. Our first two metadata entries consist of the `name` of our project and the list of authors with names and email addresses. We have used fake email addresses for this example project, but for a real project, you should use your real email address.

PyPI requires that all projects must have unique names. It is a good idea to check this when you start your project, to make sure that no other project has already used the name you want. It is also advisable to make sure your project name will not easily be confused with another; this will reduce the chances of anyone accidentally installing the wrong package.

The next entries in the `project` table are descriptions of our project:

```
# railway-project/pyproject.toml
[project]
...
description = "A CLI client for the railway API"
readme = "README.md"
```

The `description` field should be a short, single-sentence summary of the project, while `readme` should point to the README file containing a more detailed description.

The `readme` can also be specified as a TOML table, in which case it should contain a `content-type` key and either a `file` key with the path to the README file or a `text` key with the full README text.

The project's license should also be specified in the metadata:

```
# railway-project/pyproject.toml
[project]
...
license = {file = "LICENSE"}
```

The `license` field is a TOML table containing either a `file` key with the path to the license file for the project, or a `text` key with the full text of the license.

The next couple of metadata entries are meant to help potential users find our project on PyPI:

```
# railway-project/pyproject.toml
[project]
...
classifiers = [
    "Environment :: Console",
```

```
    "License :: OSI Approved :: MIT License",
    "Operating System :: MacOS",
    "Operating System :: Microsoft :: Windows",
    "Operating System :: POSIX :: Linux",
    "Programming Language :: Python :: 3",
    "Programming Language :: Python :: 3.10",
    "Programming Language :: Python :: 3.11",
    "Programming Language :: Python :: 3.12",
]
keywords = ["packaging example", "CLI"]
```

The `classifiers` field can be used to specify a list of *trove classifiers*, which are used to categorize projects on PyPI. The PyPI website allows users to filter by trove classifier when searching for projects. Your project's classifiers must be chosen from the list of official classifiers at `https://pypi.org/classifiers/`.

We have used classifiers to indicate that our project is meant to be used in a console environment, that it is released under the MIT License, that it works on macOS, Windows, and Linux, and that it is compatible with Python 3 (specifically versions 3.10, 3.11, and 3.12). Note that the classifiers are there purely to provide information to users and help them find your project on the PyPI website. They have no impact on which operating systems or Python versions your package can be installed on.

The `keywords` field can be used to provide additional keywords to help users find your project. Unlike the classifiers, there are no restrictions on what keywords you can use.

Versioning and dynamic metadata

The project metadata must contain a version number. Instead of specifying the version directly (via a `version` key), we have chosen to make the version a **dynamic field**. The `pyproject.toml` specification allows any project metadata except the `name` to be specified dynamically by other tools. The names of dynamic fields are specified via the `dynamic` key:

```
# railway-project/pyproject.toml
[project]
...
dynamic = ["version"]
```

To use dynamic metadata with Setuptools, we need to use the `tool.setuptools.dynamic` table to specify how to compute the values. The `version` can either be read from a file (specified using a table with a `file` key) or from an attribute in a Python module (specified using a table with an `attr` key). For this project, we take the version from the `__version__` attribute of the `railway_cli` importable package:

```
# railway-project/pyproject.toml
[tool.setuptools.dynamic]
version = {"attr" = "railway_cli.__version__"}
```

The `__version__` attribute is defined in the `railway_cli/__init__.py` file:

```
# railway-project/src/railway_cli/__init__.py
__version__ = "0.0.1"
```

Using a dynamic field means that we can use the same version number in our code and project metadata without needing to define it twice.

You can choose any versioning scheme that makes sense for your project, but it must comply with the rules defined in PEP 440 (`https://peps.python.org/pep-0440/`). A PEP 440-compatible version consists of a sequence of numbers, separated by dots, followed by optional pre-release, post-release, or developmental release indicators. A pre-release indicator can consist of the letter `a` (for *alpha*), `b` (for *beta*), or `rc` (for *release-candidate*), followed by a number. A post-release indicator consists of the word `post` followed by a number. A developmental release indicator consists of the word `dev` followed by a number. A version number without a release indicator is referred to as a *final* release. For example:

- `1.0.0.dev1` is the first developmental release of version 1.0.0 of our project.
- `1.0.0.a1` is the first alpha release.
- `1.0.0.b1` is the first beta release.
- `1.0.0.rc1` is the first release candidate.
- `1.0.0` is the final release of version 1.0.0.
- `1.0.0.post1` is the first post-release.

Developmental releases, pre-releases, final releases, and post-releases with the same main version number are ordered as in the list above.

Popular versioning schemes include **semantic versioning**, which aims to convey information about compatibility between releases through the versioning scheme, and **date-based versioning**, which typically uses the year and month of a release to indicate the version.

Semantic versioning uses a version number consisting of three numbers, called the *major*, *minor*, and *patch* versions, separated by dots. This results in a version that looks like `major.minor.patch`. If a new release is completely compatible with its predecessor, only the patch number is incremented; usually, such a release only contains small bug fixes. For a release that adds new functionality without breaking compatibility with previous releases, the minor number should be incremented. The major number should be incremented if the release is incompatible with older versions. You can read all about semantic versioning at `https://semver.org/`.

Specifying dependencies

As we saw at the beginning of the chapter, a distribution package can provide a list of projects it depends on, and `pip` will ensure that releases of those projects are installed when it installs the package. These dependencies should be specified in the `dependencies` key of the `project` table:

```
# railway-project/pyproject.toml
[project]
...
dependencies = [
    "pydantic[email]>=2.8.2,<3.0.0",
    "pydantic-settings~=2.4.0",
    "requests~=2.0",
]
```

Our project depends on the `pydantic`, `pydantic-settings`, and `requests` projects. The word `[email]` in square brackets for the `pydantic` dependency indicates that we also require some optional dependencies of the `pydantic` project related to dealing with email addresses. We will discuss optional dependencies in more detail in a moment.

We can use **version specifiers** to indicate which releases of dependencies we require. Besides the normal Python comparison operators, version specifiers can also use `~=` to indicate a *compatible release*. The compatible release specifier is a way of indicating releases that may be expected to be compatible under a semantic versioning scheme. For example, `requests~=2.0` means that we require any 2.x version of the `requests` project, from 2.0 up to 3.0 (not included). A version specifier can also take a comma-separated list of version clauses that must all be satisfied. For example, `pydantic>=2.8.2,<3.0.0` means that we want at least version 2.8.2 of `pydantic`, but not version 3.0.0 or greater. Note that this is not the same as `pydantic~=2.8.2`, which would mean at least version 2.8.2, but not version 2.9.0 or greater. For the full details of the dependency syntax and how versions are matched, please refer to PEP 508 (`https://peps.python.org/pep-0508/`).

You should be careful not to make your dependency version specifiers too strict. Bear in mind that your package is likely to be installed alongside various other packages in the same virtual environment. This is particularly true of libraries or tools for developers. Allowing as much freedom as possible in the required versions of your dependencies means that projects that depend on yours are less likely to encounter dependency conflicts between your package and those of other projects they depend on. Making your version specifiers too restrictive also means that your users will not benefit from bug fixes or security patches in one of your dependencies unless you also publish a new release to update your version specifier.

Apart from dependencies on other projects, you can also specify which versions of Python your project requires. In our project, we use features that were added in Python 3.10, so we specify that we require at least Python 3.10:

```
# railway-project/pyproject.toml
[project]
...
requires-python = ">=3.10"
```

As with `dependencies`, it is best to avoid limiting the Python versions you support too much. You should only restrict the Python version if you know your code will not work on all actively supported versions of Python 3.

You can find a list of *Active Python Releases* on the official Python download page: `https://www.python.org/downloads/`.

You should make sure that your code really does work on all the versions of Python and the dependencies that you support in your setup configuration. One way of doing this is to create several virtual environments with different Python versions and different versions of your dependencies installed. Then, you can run your test suite in all these environments. Doing this manually would be very time-consuming. Fortunately, there are tools that will automate this process for you. The most popular of these tools is called *tox*. You can find out more about it at `https://tox.wiki/`.

You can also specify optional dependencies for your package. `pip` will only install such dependencies if a user specifically requests it. This is useful if some dependencies are only required for a feature that many users are not likely to need. Users who want the extra feature can then install the optional dependency and everyone else gets to save disk space and network bandwidth.

For example, the PyJWT project, which we used in *Chapter 9, Cryptography and Tokens*, depends on the cryptography project to sign JWTs using asymmetric keys. Many users of PyJWT do not use this feature, so the developers made cryptography an optional dependency.

Optional (or extra) dependencies are specified in the `project.optional-dependencies` table in the `pyproject.toml` file. This section can contain any number of named lists of optional dependencies. These lists are referred to as **extras**. In our project, we have one extra called `dev`:

```
# railway-project/pyproject.toml
dev = [
    "black",
    "isort",
    "flake8",
    "mypy",
    "types-requests",
    "pytest",
    "pytest-mock",
    "requests-mock",
]
```

This is a common convention for listing tools that are useful during the development of a project as optional dependencies. Many projects also have an extra `test` dependency for installing packages that are only needed to run the project's test suite.

To include optional dependencies when installing a package, you have to add the names of the extras you want in square brackets when you run `pip install`. For example, to do an editable install of our project with the `dev` dependencies included, you can run:

```
$ pip install -e './railway-project[dev]'
```

Note that we needed to use quotes in this `pip install` command to prevent the shell from interpreting the square brackets as a filename pattern.

Project URLs

You can also include a list of URLs for websites related to your project in the `urls` sub-table of the `project` metadata table:

```
# railway-project/pyproject.toml
[project.urls]
Homepage = "https://github.com/PacktPublishing/Learn-Python-..."
"Learn Python Programming Book" = "https://www.packtpub.com/..."
```

The keys of the URLs table can be arbitrary strings describing the URLs. It is quite common for projects to include a link to their source code on a code-hosting service, such as GitHub or GitLab. Many projects also link to online documentation or bug trackers. We have used this field to add links to the source code repository for this book on GitHub and to information about the book on the publisher's website.

Scripts and entry points

So far, we have been running our application by typing:

```
$ python -m railway_cli
```

This is not particularly user-friendly. It would be much better if we could run our application by just typing:

```
$ railway-cli
```

We can achieve this by configuring script **entry points** for our distribution. A script entry point is a function that we want to be able to execute as a command-line or GUI script. When our package is installed, `pip` will automatically generate scripts that import the specified functions and run them.

We configure script entry points in the `project.scripts` table in the `pyproject.toml` file:

```
# railway-project/pyproject.toml
[project.scripts]
railway-cli = "railway_cli.cli:main"
```

Each key in this table defines the name of a script that should be generated when the package is installed. The corresponding value is an object reference pointing to the function that should be called when the script is executed. If we were packaging a GUI application, we would need to use the `project.gui-scripts` table instead.

The Windows operating system treats console and GUI applications differently. Console applications are launched in a console window and can print to the screen and read keyboard input through the console. GUI applications are launched without a console window. On other operating systems, there is no difference between `scripts` and `gui-scripts`.

Now, when we install the project in a virtual environment, `pip` will generate a `railway-cli` script in the virtual environment `bin` folder (or the `Scripts` folder on Windows). It looks like this:

```
#!/.../ch16/railway-project/venv/bin/python
# -*- coding: utf-8 -*-
```

```
import re
import sys
from railway_cli.cli import main
if __name__ == '__main__':
    sys.argv[0] = re.sub(
        r'(-script\.pyw|\.exe)?$', '', sys.argv[0]
    )
    sys.exit(main())
```

The `#!/.../ch16/railway-project/venv/bin/python` comment at the top of the file is called a **shebang** (from hash + bang – bang is another name for an exclamation mark). It specifies the path to the Python executable that will be used to run the script. The script imports the `main()` function from the `railway_cli.main` module, performs some manipulation of the program name in `sys.argv[0]`, and then calls `main()` and passes the return value to `sys.exit()`.

Apart from script entry points, it is also possible to create arbitrary entry-point groups. Such groups are defined by sub-tables under the `project.entry-points` table. `pip` will not generate scripts for entry points in other groups, but they can be useful for other purposes. Specifically, many projects that support extending their functionality via plugins use particular entry point group names for plugin discovery. This is a more advanced subject that we won't discuss in detail here, but if you are interested, you can read about it in the entry-points specification: `https://packaging.python.org/specifications/entry-points/`.

Defining the package contents

For projects that use the src layout, Setuptools can usually automatically determine which Python modules to include in the distribution. For flat layouts, automatic discovery only works if there is only one importable package present in the project folder. If there are any other Python files present, you will need to configure the packages and modules to include or exclude via the `tools.setuptools` table in `pyproject.toml`.

If you use an src layout, you only need additional configuration if you use a name other than `src` for the folder containing the code, or if there are some modules in the `src` folder that need to be excluded from the distribution. In our railway-cli project, we rely on automatic discovery, so we do not have any package discovery configuration in our `pyproject.toml` file. You can read more about Setuptools's automatic discovery and how to customize it in the Setuptools user guide: `https://setuptools.pypa.io/en/latest/userguide/`.

Our package metadata configuration is now complete. Before we move on to building and publishing a package, we will take a brief look at how we can access the metadata in our code.

Accessing metadata in your code

We have already seen how we can use dynamic metadata to share the version number between the distribution configuration and the code. For other dynamic metadata, Setuptools only supports loading from files, not from attributes in the code. Such files will not be included in the wheel distribution unless we add explicit configuration for this. There is, however, a more convenient way to access distribution metadata from the code.

The `importlib.metadata` standard library module provides interfaces to access the distribution metadata of any installed package. To demonstrate this, we have added a command-line option for displaying the project license to the Railway CLI application:

```
from importlib.metadata import metadata, packages_distributions

def get_arg_parser() -> argparse.ArgumentParser:
    ...
    parser.add_argument(
        "-L",
        "--license",
        action="version",
        version=get_license(),
    )
    ...

def get_license() -> str:
    default = "License not found"

    all_distributions = packages_distributions()
    try:
        distribution = all_distributions[__package__][0]
    except KeyError:
        return default

    meta = metadata(distribution)
    return meta["License"] or default
```

We use the `"version"` argument parser action to print the license string and exit if the `-L` or `--license` option is present on the command line. To get the license text, we first need to find the distribution corresponding to our importable package. The `packages_distributions()` function returns a dictionary whose keys are the names of importable packages in the virtual environment. The values are lists of distribution packages that provide the corresponding importable packages. We assume that no other installed distributions provide a package of the same name as ours, so we just take the first element of the `all_distributions[__package__]` list.

The `metadata` function returns a `dict`-like object with the metadata. The keys are similar to, but not quite the same as, the names of the `pyproject.toml` entries we use to define the metadata. Details of all the keys and their meanings can be found in the metadata specification at `https://packaging.python.org/specifications/core-metadata/`.

Note that if our package is not installed, we will get a `KeyError` when we try to look it up in the dictionary returned by `packages_distributions()`. In this case, or in the case where there is no `"License"` specified in the project metadata, we return a default value to indicate that the license could not be found.

Let us see what the output looks like:

```
$ railway-cli -L
Copyright (c) 2024 Heinrich Kruger, Fabrizio Romano

Permission is hereby granted, free of charge, ...
```

We have trimmed the output here to save space, but if you run it yourself, you should see the full license text printed out.

Now, we are ready to proceed with building and publishing distribution packages.

Building and publishing packages

We will use the package builder provided by the *build* project (`https://pypi.org/project/build/`) to build our distribution package. We will also need the *twine* (`https://pypi.org/project/twine/`) utility to upload our packages to PyPI. You can install these tools from the `requirements/build.txt` file provided with the source code of this chapter. We recommend installing these in a new virtual environment.

Because project names on PyPI must be unique, you will not be able to upload the `railway-cli` project without changing the name first. You should change the `name` in the `pyptoject.toml` file to something unique before building distribution packages. Bear in mind that this means that the filenames of your distribution packages will also be different from ours.

Building

The `build` project provides a simple script for building packages according to the PEP 517 specification. It will take care of all the details of building distribution packages for us. When we run it, `build` will do the following:

1. Create a virtual environment.
2. Install the build requirements listed in the `pyproject.toml` file in the virtual environment.
3. Import the build backend specified in the `pyproject.toml` file and run it to build a source distribution.
4. Create another virtual environment and install the build requirements.
5. Import the build backend and use it to build a wheel from the source distribution built in *step 3*.

Let us see it in action. Enter the `railway-project` folder in the chapter's source code, and run the following command:

```
$ python -m build
* Creating isolated environment: venv+pip...
* Installing packages in isolated environment:
  - setuptools>=66.1.0
  - wheel
* Getting build dependencies for sdist...
...
* Building sdist...
...
* Building wheel from sdist
* Creating isolated environment: venv+pip...
* Installing packages in isolated environment:
  - setuptools>=66.1.0
```

```
  - wheel
* Getting build dependencies for wheel...
...
* Building wheel...
...
Successfully built railway_cli-0.0.1.tar.gz and
railway_cli-0.0.1-py3-none-any.whl
```

We have removed a lot of lines from the output to make it easier to see how it follows the steps we listed above. If you look at the content of your `railway-project` folder, you will notice there is a new folder called `dist` with two files: `railway_cli-0.0.1.tar.gz` is our source distribution, and `railway_cli-0.0.1-py3-none-any.whl` is the wheel.

Before uploading your package, it is advisable to do a couple of checks to make sure it is built correctly. First, we can use `twine` to verify that the `readme` will render correctly on the PyPI website:

```
$ twine check dist/*
Checking dist/railway_cli-0.0.1-py3-none-any.whl: PASSED
Checking dist/railway_cli-0.0.1.tar.gz: PASSED
```

If `twine` reports any problems, you should fix them and rebuild the package. In our case, the checks passed, so let us install our wheel and make sure it works. In a separate virtual environment, run:

```
$ pip install dist./railway_cli-0.0.1-py3-none-any.whl
```

With the wheel installed in your virtual environment, try to run the application, preferably from outside the project directory. If you encounter any errors during installation or when running your code, check your configuration carefully for typos.

Our package seems to have been built successfully, so let us move on to publishing it.

Publishing

Since this is only an example project, we will upload it to TestPyPI instead of the real PyPI. This is a separate instance of the package index that was created specifically to allow developers to test package uploads and experiment with packaging tools and processes.

Before you can upload packages, you will need to register an account. You can do this now, by going to the TestPyPI website at `https://test.pypi.org` and clicking on **Register**. Once you have completed the registration process and verified your email address, you will need to generate an API token. You can do so on the **Account Settings** page of the TestPyPI website. Make sure you copy the token and save it before closing the page. You should save your token to a file named `.pypirc` in your user home directory. The file should look like this:

```
[testpypi]
  username = __token__
  password = pypi-...
```

The `password` value should be replaced with your actual token.

We strongly recommend that you enable two-factor authentication for both your TestPyPI account and especially your real PyPI account.

Now, you are ready to run `twine` to upload your distribution packages:

```
$ twine upload --repository testpypi dist/*
Uploading distributions to https://test.pypi.org/legacy/
Uploading railway_cli-0.0.1-py3-none-any.whl
100% ━━━━━━━━━━━━━━━━━━━━ 19.3/19.3 kB • 00:00 • 7.3 MB/s
Uploading railway_cli-0.0.1.tar.gz
100% ━━━━━━━━━━━━━━━━━━━━ 17.7/17.7 kB • 00:00 • 9.4 MB/s

View at:
https://test.pypi.org/project/railway-cli/0.0.1/
```

`twine` displays progress bars to show how the uploads are progressing. Once the upload is complete, it prints out a URL where you can see details of your package. Open it in your browser, and you should see our project description with the contents of our `README.md` file. On the left of the page, you will see links for the project URLs, the author details, license information, keywords, and classifiers.

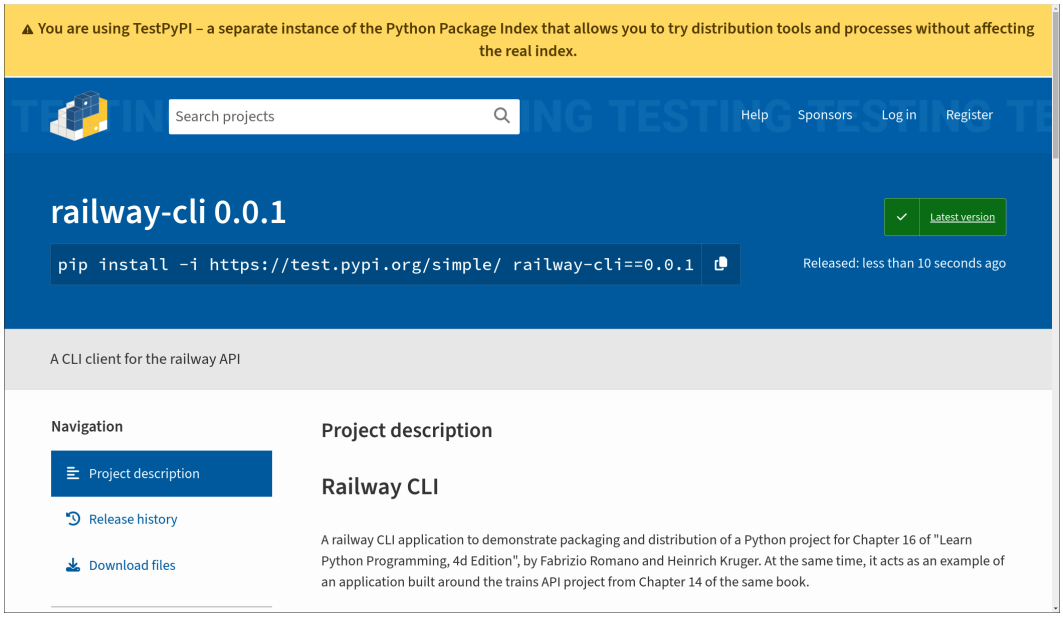

Figure 16.1: Our project page on the TestPyPI website

Figure 16.1 shows what this page looks like for our railway-cli project. You should check all the information on the page carefully and make sure it matches what you expect to see. If not, you will have to fix the metadata in your `pyproject.toml`, rebuild, and re-upload.

PyPI will not let you re-upload distributions with the same filenames as previously uploaded packages. To fix your metadata, you will have to increment the version of your package. Using developmental release numbers until you are 100% sure everything is correct can help you avoid unnecessary version increments just to fix packaging mistakes.

Now, we can install our package from the TestPyPI repository. Run the following in a new virtual environment:

```
pip install --index-url https://test.pypi.org/simple/ \
    --extra-index-url https://pypi.org/simple/ railway-cli==1.0.0
```

The `--index-url` option tells `pip` to use `https://test.pypi.org/simple/` as the main package index. We use `--extra-index-url https://pypi.org/simple/` to tell `pip` to also look up packages in standard PyPI so that dependencies that are not available in TestPyPI can be installed. The package was installed successfully, which confirms that our package was built and uploaded correctly.

If this were a real project, we would now proceed to upload to the real PyPI. The process is the same as for TestPyPI. When you save your PyPI API key, you should add it to your existing `.pypirc` file under the heading `[pypi]`, like this:

```
[pypi]
  username = __token__
  password = pypi-…
```

You also do not need to use the `--repository` option to upload your package to the real PyPI; you can just run the following:

```
$ twine upload dist/*
```

As you can see, it is not difficult to package and publish a project, but there are quite a few details to take care of. The good news is that most of the work only needs to be done once: when you publish your first release. For subsequent releases, you usually just need to update the version and maybe adjust your dependencies. In the next section, we will give you some advice that should make the process easier.

Advice for starting new projects

It can be a tedious process to do all the preparation work for packaging in one go. It is also easy to make a mistake like forgetting to list a required dependency if you try to write all your package configurations just before publishing your package for the first time. It is much easier to start with a simple `pyproject.toml`, containing only the essential configuration and metadata. You can then add to your metadata and configuration as you work on your project. For example, every time you start using a new third-party project in your code, you can immediately add it to your `dependencies` list. It also helps to start writing your README file early on and then expanding it as you progress. You may even find that writing a paragraph or two describing your project helps you to think more clearly about what it is you are trying to achieve.

To help you, we have created an initial skeleton for a new project. You can find it in the `skeleton-project` folder in this chapter's source code:

```
$ tree skeleton-project
skeleton-project
├── README.md
├── pyproject.toml
├── src
│   └── example
```

```
│       └── __init__.py
└── tests
    └── __init__.py
```

Copy this, modify it as you wish, and use it as a starting point for your own projects.

The cookiecutter project (`https://cookiecutter.readthedocs.io`) allows you to create templates to use as starting points for projects. This can make the process of starting a new project much simpler.

Other files

The configuration files we showed you in this chapter are all you need to package and distribute most modern Python projects. There are, however, a few other files that you are likely to encounter if you look at other projects on PyPI:

- In early versions of Setuptools, every project needed to include a setup.py script, which was used to build the project. Most such scripts consisted only of a call to the `setuptools.setup()` function with project metadata specified as parameters. The use of `setup.py` has not been deprecated and this is still a valid method of configuring Setuptools.
- Setuptools also supports reading its configuration from a `setup.cfg` file. Before the widespread adoption of `pyproject.toml`, this was the preferred way of configuring Setuptools.
- If you need to include data files or other non-standard files in your distribution packages, you will need to use a `MANIFEST.in` file to specify the files to include. You can learn more about the use of this file at `https://packaging.python.org/guides/using-manifest-in/`.

Alternative tools

Before we finish the chapter, let us briefly discuss some alternative options that you have for packaging your projects. Before PEP 517 and PEP 518, it was difficult to use anything other than Setuptools to build packages. There was no way for projects to specify what libraries were required to build them or how they should be built, so `pip` and other tools just assumed that packages should be built using Setuptools.

Thanks to the build-system information in the `pyproject.toml` file, it is now easy to use any packaging library you want. There are several alternatives to choose from, including:

- The Flit project (`https://flit.pypa.io`) was instrumental in inspiring the development of the PEP 517 and PEP 518 standards (the creator of Flit was a co-author of PEP 517). Flit aims to make packaging simple, pure Python projects that do not require complex build steps (like compiling C code) as easy as possible. Flit also provides a CLI for building packages and uploading them to PyPI (so you do not need the `build` tool or `twine`).
- Poetry (`https://python-poetry.org/`) also provides both a CLI for building and publishing packages and a lightweight PEP 517 build backend. Where Poetry really shines, though, is in its advanced dependency management features. Poetry can even manage virtual environments for you.
- Hatch (`https://hatch.pypa.io`) is an extensible project manager tool for Python. It includes tools for installing and managing Python versions, managing virtual environments, running tests, and more. It also includes a PEP 517 build backend named hatchling.
- PDM (`https://pdm-project.org/`) is another package and dependency manager that includes a build backend. Like Hatch, it can be used to manage virtual environments and install Python versions. There are also many plugins available to extend PDM's functionality.
- Enscons (`https://dholth.github.io/enscons/`) is based on the SCons (`https://scons.org/`) general-purpose build system. This means that, unlike Flit or Poetry, enscons can be used to build distributions that include C language extensions.
- Meson (`https://mesonbuild.com/`) is another popular general-purpose build system. The `meson-python` (`https://mesonbuild.com/meson-python/`)project provides a PEP 517 build backend that is built on top of Meson. This means that it can build distributions that include extension modules built with Meson.
- Maturin (`https://www.maturin.rs/`) is another build tool that can be used to build distributions with extension modules implemented in the Rust programming language.

The tools we have discussed in this chapter are all focused on distributing packages through PyPI. Depending on your target audience, this might not always be the best choice, though. PyPI exists mainly for distributing projects such as libraries and development tools for use by Python developers. Installing and using packages from PyPI also requires having a working Python installation and at least enough Python knowledge to know how to install packages with `pip`.

If your project is an application aimed at a less technically adept audience, you may want to consider other options. The Python Packaging User Guide has a useful overview of various options for distributing applications; it is available at `https://packaging.python.org/overview/#packaging-applications`.

This brings us to the end of our packaging journey.

Further reading

We will finish this chapter with a few links to resources where you can read more about packaging:

- The Python Packaging Authority's Packaging History page (`https://www.pypa.io/en/latest/history/`) is a useful resource for understanding the evolution of Python packaging.
- The Python Packaging User Guide (`https://packaging.python.org/`) has useful tutorials and guides, as well as a packaging glossary, links to packaging specifications, and a summary of various interesting projects related to packaging.
- The Setuptools documentation (`https://setuptools.readthedocs.io/`) contains a lot of useful information.
- If you are distributing a library that uses type hinting, you may want to distribute type information so that developers who depend on your library can run type checks against their code. The Python typing documentation includes some useful information on distributing type information: `https://typing.readthedocs.io/en/latest/spec/distributing.html`.
- In this chapter, we showed you how to access distribution metadata in your code. Most packaging tools also allow you to include data files in your distribution packages. The standard library `importlib.resources` module provides access to these **package resources**. You can read about it at `https://docs.python.org/3/library/importlib.resources.html`.

As you read about these (and other packaging resources), it is worth bearing in mind that although PEP 517, PEP 518, and PEP 621 were finalized a few years ago, many projects have not fully migrated to using PEP 517 builds, or configuring project metadata in `pyproject.toml` files. Much of the available documentation also still refers to older ways of doing things.

Summary

In this chapter, we looked at how to package and distribute Python projects through PyPI. We started with some theory about packaging and introduced the concepts of projects, releases, and distributions on PyPI.

We learned about Setuptools, the most widely used packaging library for Python, and worked through the process of preparing a project for packaging with Setuptools. In the process, we saw various files that need to be added to a project to package it and what each of them is for.

We discussed the metadata that you should provide to describe your project and help users find it on PyPI, as well as how to add code to the distribution, how to specify our dependencies, and how to define entry points so that `pip` will automatically generate scripts for us. We also looked at the tools that Python provides for accessing the distribution metadata.

We moved on to talking about how to build distribution packages and how to use `twine` to upload those packages to PyPI. We also gave you some advice on starting new projects. We concluded our tour of packaging by briefly talking about some alternatives to Setuptools and pointing you to some resources where you can learn more about packaging.

We really do encourage you to start distributing your code on PyPI. No matter how trivial you think it might be, someone else somewhere in the world will probably find it useful. It really does feel good to contribute and give back to the community, and besides, it looks good on your CV.

The next chapter will introduce you to the world of competitive programming. We are going to deviate a little bit from professional programming to learn a few things about programming challenges and why they can be so much fun, and useful, too.

Join our community on Discord

Join our community's Discord space for discussions with the authors and other readers:

`https://discord.com/invite/uaKmaz7FEC`

17

Programming Challenges

> *"Beware of bugs in the above code; I have only proved it correct, not tried it."*
>
> *– Donald Knuth*

In this chapter, we are going to deviate from professional programming and discuss the world of competitive programming and **programming challenges**.

Programming challenges are problems that can be solved with a relatively short program. There are several websites that offer great collections of challenges. Most of them categorize challenges based on difficulty and other factors, such as:

- The type of algorithm needed to solve the challenges.
- The type of abstract data structures the challenges are about, like trees, linked lists, n-dimensional vectors, and so on.
- The type of concrete data structures the challenges are about. For example, for Python, they could be lists, tuples, dictionaries, and so on.
- The type of approach needed to solve the challenges, such as dynamic programming, recursion, and so on.

This list is not fully comprehensive, but it gives an idea of what we can expect.

Websites that offer programming challenges do it for various reasons. Some help programmers prepare for interviews, others do it for mere leisure, and others again do it as a way to teach programming.

Some websites also host competitions, where the solutions provided by the participants are measured on execution speed, correctness, and memory footprint, just to name a few.

The world of competitive programming is quite fun, and programming challenges are an excellent way to learn new languages and improve your programming skills.

In this chapter, we are going to solve two problems from **Advent of Code** (`https://adventofcode.com/`), which is our favorite challenge website. Solving challenges is fun, and it is an efficient way for us to showcase several features of Python in a relatively short amount of code.

Advent of Code

Advent of Code was created by Eric Wastl in 2015. Quoting from the website:

> *"Advent of Code is an Advent calendar of small programming puzzles for a variety of skill sets and skill levels that can be solved in any programming language you like. People use them as interview prep, company training, university coursework, practice problems, a speed contest, or to challenge each other.*
>
> *You don't need a computer science background to participate - just a little programming knowledge and some problem-solving skills will get you pretty far. Nor do you need a fancy computer; every problem has a solution that completes in at most 15 seconds on ten-year-old hardware."*

Every problem has two parts. According to Eric, the first one is a way to make sure that you understand the assignment, and the second one is the actual problem. The second part is normally more challenging than the first one. Each problem is accompanied by input data that you can download from the website.

This website has some peculiar characteristics. Firstly, every problem is part of a story where the programmer – by solving the challenges – helps either Santa Claus or his helpers, the Elves, save Christmas. Each problem is therefore part of an adventure that lasts 25 days, from December 1st to December 25th. The presentation is infused with humor and each problem is unique and requires some degree of both logical and creative thinking. This is not that common a thing on many other similar websites, where challenges are normally much dryer, and their solutions often revolve around applying certain algorithms or using the appropriate data structures or patterns.

Before deciding to add this chapter, we spoke to Eric, and his only request was that we would not reproduce the full challenges verbatim. In accordance with that, we have abridged the problem statements so that we present only the problem instructions.

The solutions we are about to present are just one of the several ways in which these challenges can be solved. They are designed to allow us to discuss a few final concepts with you. Our advice is: after you have read this chapter, try and come up with your own solutions to the problems presented.

Let us start.

Camel Cards

The first problem, *Camel Cards*, is from day 7, 2023. In this challenge, which you can find at `https://adventofcode.com/2023/day/7`, we have to write a program that solves a variant of the poker game.

Part one — problem statement

This is an abridged version of the original text:

"In Camel Cards, you get a list of hands, and your goal is to order them based on the strength of each hand. A hand consists of five cards labeled one of `A`, `K`, `Q`, `J`, `T`, `9`, `8`, `7`, `6`, `5`, `4`, `3`, or `2`. The relative strength of each card follows this order, where `A` is the highest and `2` is the lowest.

Every hand is exactly one type. From strongest to weakest, they are:

- **Five of a kind**, where all five cards have the same label: `AAAAA`.
- **Four of a kind**, where four cards have the same label, and one card has a different label: `AA8AA`.
- **Full house**, where three cards have the same label, and the remaining two cards share a different label: `23332`.
- **Three of a kind**, where three cards have the same label, and the remaining two cards are each different from any other card in the hand: `TTT98`.
- **Two pair**, where two cards share one label, two other cards share a second label, and the remaining card has a third label: `23432`.
- **One pair**, where two cards share one label, and the other three cards have a different label from the pair and each other: `A23A4`.
- **High card**, where all cards' labels are distinct: `23456`.

Hands are primarily ordered based on type; for example, every full house is stronger than any three of a kind.

If two hands have the same type, a second ordering rule takes effect. Start by comparing the first card in each hand. If these cards are different, the hand with the stronger first card is considered stronger. If the first card in each hand has the same label, however, then move on to considering the second card in each hand. If they differ, the hand with the higher second card wins; otherwise, continue with the third card in each hand, then the fourth, then the fifth.

So, `33332` and `2AAAA` are both *four of a kind* hands, but `33332` is stronger because its first card is stronger. Similarly, `77888` and `77788` are both a full house, but `77888` is stronger because its third card is stronger (and both hands have the same first and second card).

To play Camel Cards, you are given a list of hands and their corresponding bid (your puzzle input). For example:

```
32T3K 765
T55J5 684
KK677 28
KTJJT 220
QQQJA 483
```

This example shows five hands; each hand is followed by its bid amount. Each hand wins an amount equal to its bid multiplied by its rank, where the weakest hand gets rank 1, the second-weakest hand gets rank 2, and so on up to the strongest hand. Because there are five hands in this example, the strongest hand will have rank 5 and its bid will be multiplied by 5.

So, the first step is to put the hands in order of strength:

- `32T3K` is the only one-pair hand, and the other hands are all a stronger type, so it gets rank 1.
- `KK677` and `KTJJT` are both two pair. Their first cards both have the same label, but the second card of `KK677` is stronger (`K` vs `T`), so `KTJJT` gets rank 2 and `KK677` gets rank 3.
- `T55J5` and `QQQJA` are both three of a kind. `QQQJA` has a stronger first card, so it gets rank 5 and `T55J5` gets rank 4.
- Now, you can determine the total winnings of this set of hands by adding up the result of multiplying each hand's bid with its rank (`765 * 1 + 220 * 2 + 28 * 3 + 684 * 4 + 483 * 5`). So, the total winnings in this example are `6440`.

Find the rank of every hand in your set. What are the total winnings?"

Our job is to find the total winnings following the given instructions.

Part one — solution

The implementation of the solution is straightforward. Because part two of the problem is fairly similar to part one, we have encapsulated the common logic into one base class, `Solver`. This class provides all the methods we need to solve the problem, apart from one, `type()`, which is implemented in each of the child classes, `PartOne` and `PartTwo`. This is just one of many possible approaches to preventing code duplication. Let us see the first part of the code:

```
# day7.py
from collections import Counter
from functools import cmp_to_key
from util import get_input

class Solver:
    strengths: str = ""

    def __init__(self) -> None:
        self.ins: list[str] = get_input("input7.txt")

    def solve(self) -> int:
        hands = dict(self.parse_line(line) for line in self.ins)
        sorted_hands = sorted(
            hands.keys(), key=cmp_to_key(self.cmp)
        )
        return sum(
            rank * hands[hand]
            for rank, hand in enumerate(sorted_hands, start=1)
        )

    def parse_line(self, line: str) -> tuple[str, int]:
        hand, bid = line.split()
        return hand, int(bid)
```

We import `Counter` and `cmp_to_key()` from the standard library and `get_input()` from the `util.py` module. The latter is a helper that reads the input file and returns a list of strings, like `["9A35J 469", "75T32 237", ...]`.

We define the `Solver` class, which is only partially reproduced here, which reads in the inputs during the initialization and contains the `solve()` method, which runs the algorithm. The steps are simple: we use the `parse_line()` method to convert from a list of strings to a dictionary (`hands`) whose keys are the hands, and whose values are their respective bids, already converted to integers.

After converting the input data, we create a list of hands, sorted by their rank, which is calculated according to the rules given by the problem statement. We will analyze the custom `cmp()` method in a moment. For now, just notice how it is used, to perform the sorting. Since a comparator takes two objects to compare, it is not suitable as an argument to the `key` parameter of the `sorted()` function. For this reason, Python provides the `cmp_to_key()` function, which takes a comparator function as input and produces an object that can be used as a key for sorting.

After creating a sorted list of hands, we return the sum of all the products between each hand's rank, and its bid.

Let us examine the more interesting part of this class now:

```
# day7.py
…
class Solver:
    …
    def type(self, hand: str) -> list[int]:
        raise NotImplementedError

    def cmp(self, hand1: str, hand2: str) -> int:
        """-1 if hand1 < hand2 else 1, or 0 if hand1 == hand2"""
        type1 = self.type(hand1)
        type2 = self.type(hand2)
        if type1 == type2:
            for card1, card2 in zip(hand1, hand2):
                strength1 = self.strengths.index(card1)
                strength2 = self.strengths.index(card2)
                if strength1 == strength2:
                    continue
                return -1 if strength1 < strength2 else 1
            return 0
        return -1 if type1 < type2 else 1
```

In the rest of the class code, we defined the custom comparator `cmp()`. It takes two hands and performs the comparison according to the problem's rules. First, we calculate the type of each hand. If the types are different, we return `-1` if `hand2` is stronger than `hand1`, or `1` in the opposite case. Should the type of both hands be the same, we need to check the strength of each card. Depending on the result of this check, we return `-1` or `1` using the same criteria as before. For completeness, if both the type and strength of the two hands are the same, we return `0`. We know, from the problem statement, that this latter scenario is never going to happen, otherwise the final ranking might depend on the input order.

The comparator is using the `type()` method, whose logic is not implemented in this class. Since the strengths of the card and the calculation of the hands' types is what changes between part one and part two, we implement them in two dedicated classes.

Let us see the implementation for `PartOne`:

```
# day7.py
…
class PartOne(Solver):
    strengths: str = "23456789TJQKA"

    def type(self, hand: str) -> list[int]:
        return [count for _, count in Counter(hand).most_common()]
```

In `PartOne`, we set the `strengths` class attribute and implement the `type()` method. When we call it with a few example hands, these are the results:

```
type("KK444") = [3, 2]
type("QQQ6Q") = [4, 1]
type("5JA22") = [2, 1, 1, 1]
type("7A264") = [1, 1, 1, 1, 1]
type("TTKTT") = [4, 1]
```

This is how `type()` works: the hand is first fed to a `Counter`. This object will count how many occurrences there are of each character in the hand. In the first example, the result of `Counter("KK444")` is `{'K': 2, '4': 3}`, which is a *dict-like* object. As expected, we have two `K`s and three `4`s. Using the `most_common()` method, we can get a list of the values of that object, sorted from highest to lowest. This will produce the result in the example above: `[3, 2]`. Those lists, `[1, 1, 1, 1, 1]`, `[3, 2]`, `[4, 1]`, and so on, can be compared to one another to calculate the ranks. We do this when we calculate `sorted_hands` in the `solve()` method.

Now, it is time to create an instance of `PartOne` and run its `solve()` method:

```
# day7.py
part_one = PartOne()
print(part_one.solve())
```

Notice that we set `PartOne.strengths` to the string `"23456789TJQKA"`. That is the order in which strengths are to be evaluated, according to the problem statement, with `2` being the weakest and `A` being the strongest. Expressing their relative weight using their position is what enabled us to compare them, within `cmp()`, by using their index in the string. The higher the index, the stronger the card.

Part one is now concluded, so let us move on to part two.

Part two — problem statement

When we input the correct solution for part one on the website, we can access part two. Now the rules are changing a little bit because the joker card is introduced in the game.

> "Now, `J` cards are jokers – wildcards that can act like whatever card would make the hand the strongest type possible. To balance this, `J` cards are now the weakest individual cards, weaker even than `2`. The other cards stay in the same order: `A`, `K`, `Q`, `T`, `9`, `8`, `7`, `6`, `5`, `4`, `3`, `2`, `J`.
>
> `J` cards can pretend to be whatever card is best for the purpose of determining hand type; for example, `QJJQ2` is now considered four of a kind. However, for the purpose of breaking ties between two hands of the same type, `J` is always treated as `J`, not the card it is pretending to be: `JKKK2` is weaker than `QQQQ2` because `J` is weaker than `Q`.

Now, the above example goes very differently:

```
32T3K 765
T55J5 684
KK677 28
KTJJT 220
QQQJA 483
```

- `32T3K` is still the only one-pair hand; it does not contain any jokers, so its strength does not increase.
- `KK677` is now the only two pair, making it the second-weakest hand.
- `T55J5`, `KTJJT`, and `QQQJA` are now all four of a kind! `T55J5` gets rank 3, `QQQJA` gets rank 4, and `KTJJT` gets rank 5.

With the new joker rule, the total winnings in this example are `5905`. Using the new joker rule, find the rank of every hand in your set. What are the new total winnings?"

Let us dive into the solution.

Part two — solution

For this part, we only need to provide the correct new set of strengths and a different implementation of the `type()` method.

Let us see the code, which is a continuation from the same module:

```
# day7.py
…
class PartTwo(Solver):
    strengths: str = "J23456789TQKA"

    def type(self, hand: str) -> list[int]:
        card_counts = Counter(hand.replace("J", "")).most_common()
        h = [count for _, count in card_counts]
        return [h[0] + hand.count("J"), *h[1:]] if h else [5]

part_two = PartTwo()
print(part_two.solve())
```

The above is all we need to solve the second part of the problem. The new version of the `type()` method works in this way: we still feed the `hand` string to a `Counter` but, this time, we remove any jokers from the hand. We sort the values in reverse order again, using the `most_common()` method. At this point, we end up in one of these scenarios:

- For a hand solely made of jokers, `"JJJJJ"`, `h` will be empty, so `type()` returns `[5]`. This is correct because the highest rank given this hand is a *five of a kind*.
- For a hand with no jokers, the logic behaves like that of `PartOne.type()`.
- For a hand with at least one joker, but less than five, we first calculate its type ignoring the jokers. After that, we return an amended version of that result, where the first element is incremented by the number of jokers in the hand. For example, the hand `"KKJJ4"` will produce (ignoring the jokers) the list `[2, 1]` (two `K`s and one `4`). The smartest thing to do, to maximize its rank, is to use the two jokers as if they were `K`s. That would mean having the equivalent hand `"KKKK4"`. To do this, we add 2 (the number of jokers) to the first element in the list `[2, 1]`, so we return `[4, 1]`, which is the correct type for the `"KKKK4"` hand.

The only other important detail in `PartTwo` is the new strengths, which are now `"J23456789TQKA"`. For this part, the strengths also consider the joker card, which is the weakest, and therefore goes at the lowest index in the string.

This concludes the second part of the problem. We chose this problem because it allowed us to show you how you can use OOP to prevent the duplication of code, as well as for the use of `Counter` and `cmp_to_key()`.

You can find the inputs for this problem in the `ch17` folder of the book's source code, as well as the implementation of the `get_input()` function, in the `util.py` module.

Now, let's move on to the second challenge.

Cosmic Expansion

The second problem, *Cosmic Expansion*, is from day 11, 2023. In this challenge, which you can find at `https://adventofcode.com/2023/day/11`, we need to expand a universe and calculate the length of the shortest path between all pairs of galaxies.

Part one — problem statement

Here is an abridged version of the original text:

"The researcher has collected a bunch of data and compiled the data into a single giant image (your puzzle input). The image includes empty space (`.`) and galaxies (`#`). For example:

```
...#......
.......#..
#.........
..........
......#...
.#........
.........#
..........
.......#..
#...#.....
```

The researcher is trying to figure out the sum of the lengths of the shortest path between every pair of galaxies. However, there is a catch: the universe expanded in the time it took the light from those galaxies to reach the observatory.

Only some space expands. In fact, any rows or columns that contain no galaxies should all be twice as big. In the above example, three columns and two rows contain no galaxies. These rows and columns need to be twice as big; the result of cosmic expansion therefore looks like this:

```
....#........
.........#...
#............
.............
.............
........#....
.#...........
............#
.............
.............
.........#...
#....#.......
```

Equipped with this expanded universe, the shortest path between every pair of galaxies can be found. It can help to assign every galaxy a unique number. In these 9 galaxies, there are 36 pairs. Only count each pair once; order within the pair does not matter. For each pair, find any shortest path between the two galaxies using only steps that move up, down, left, or right exactly one • or # at a time. (The shortest path between two galaxies is allowed to pass through another galaxy.)

Assigning unique numbers, and highlighting with *x's* one of the shortest paths from galaxy 5 to galaxy 9, we get this:

```
....1........
.........2...
3............
.............
.............
........4....
.5...........
.xx.........6
..xx.........
...xx........
....xx...7...
8....9.......
```

It takes a minimum of 9 steps to get from galaxy 5 to galaxy 9 (the 8 *x's* plus the step onto galaxy 9 itself). Here are some other examples of shortest path lengths:

Between galaxy 1 and galaxy 7: 15

Between galaxy 8 and galaxy 9: 5

In this example, after expanding the universe, the sum of the shortest path between all 36 pairs of galaxies is 374. Expand the universe, then find the length of the shortest path between every pair of galaxies. What is the sum of these lengths?"

Let us now see the solution for this part.

Part one — solution

Let us start by defining the basic blocks:

```
# day11.py
from itertools import combinations
from typing import NamedTuple, Self
from util import get_input

universe = get_input("input11.txt")

class Galaxy(NamedTuple):
    x: int
    y: int

    @classmethod
    def expand(
        cls, galaxy: Self, xfactor: int, yfactor: int
    ) -> Self:
        return cls(galaxy.x + xfactor, galaxy.y + yfactor)

    @classmethod
    def manhattan(cls, a: Self, b: Self) -> int:
        return abs(a.x - b.x) + abs(a.y - b.y)

class ExpansionCoeff(NamedTuple):
    x: int = 0
    y: int = 0
```

The code begins with some imports. We will need to calculate all pairs of galaxies, which can be accomplished with `itertools.combinations()`. We also need `NamedTuple` and `Self`, from the `typing` module, and, of course, our custom `get_input()` function to read the input file, which we assign the name `universe`.

In this problem, we have chosen to create a `Galaxy` class, which represents a point in space. It inherits from `NamedTuple`, which provides some helpful features out of the box. Other suitable choices for this data are `dataclasses.dataclass`, `complex`, or even just a bare custom class.

`Galaxy` has two coordinates, `x` and `y`; it defines an `expand()` method, which returns a new `Galaxy` with shifted coordinates, and a `manhattan()` method, which calculates the distance between two galaxies using **Taxicab Geometry**. To learn more about it, please visit `https://en.wikipedia.org/wiki/Taxicab_geometry`. Suffice it to say, it is the way in which distances are calculated when movement is constrained to the vertical and horizontal directions on an integer plane.

We also define an `ExpansionCoeff` class to represent an expansion coefficient.

Here is the main part of the solver logic:

```
# day11.py
…
def coords_to_expand(universe: list[str]) -> list[int]:
    return [
        coord
        for coord, row in enumerate(universe)
        if set(row) == {"."}
    ]

def expand_universe(universe: list[str], coeff: int) -> set:
    galaxies = parse(universe)

    rows_to_expand = coords_to_expand(universe)
    galaxies = expand_dimension(
        galaxies, rows_to_expand, ExpansionCoeff(y=coeff - 1)
    )

    transposed_universe = ["".join(col) for col in zip(*universe)]
    cols_to_expand = coords_to_expand(transposed_universe)
    return expand_dimension(
```

```
            galaxies, cols_to_expand, ExpansionCoeff(x=coeff - 1)
        )

    def parse(ins: list[str]) -> set:
        return {
            Galaxy(x, y)
            for y, row in enumerate(ins)
            for x, val in enumerate(row)
            if val == "#"
        }

    def solve(universe: list[str], coeff) -> int:
        expanded_universe = expand_universe(universe, coeff)
        return sum(
            Galaxy.manhattan(g1, g2)
            for g1, g2 in combinations(expanded_universe, 2)
        )
```

The `solve()` function calculates the expanded universe and returns the sum of the shortest paths between each pair. The main task is performed in the `expand_universe()` method.

Here, we first parse the universe, to extract a set of `Galaxy` instances. Expansion is performed in two steps: first, we expand along the vertical direction, then the horizontal. Because the universe is a list of strings, it can be seen as a two-dimensional matrix. To expand it along two orthogonal directions we have two choices: one would be to write a separate function for each direction and call them passing the universe as an argument. The second option, which is what we implemented, is to write the expansion code only for the vertical direction and call it once with the universe as it is, and once more passing the transposed version of the universe. This does the equivalent job of expanding along the horizontal direction.

If you are not familiar with the concept of a transposed matrix, you can learn about it at `https://en.wikipedia.org/wiki/Transpose`. Simply put, the transposed version of a matrix is the result of flipping that matrix over its diagonal. The result has the original rows as columns, and vice versa.

In the highlighted row, you can see how the transposed version of the universe is calculated. We could have used just `zip(*universe)`, but that would have required some tweaking to the type annotations, as that does not return a list of strings. We opted to comply with simpler type annotations and created the transposed version of the universe as a list of strings instead for consistency with the original version of the universe.

It is worth mentioning that, in professional code, the better choice would be to adapt annotations to the code, rather than the other way around, but in this case, we wanted to keep things as simple as possible, in terms of readability.

One word about the `coords_to_expand()` method. The algorithm we implemented to expand the universe in a direction relies on the fact that the coordinates to expand are sorted. You can see that, by looping on the universe from top to bottom and returning a list of coordinates of the rows that contain no galaxies, we are still producing a sorted list without explicitly having to call `sorted()` on it.

The last bit of code we need is the part that does the one-dimensional expansion:

```
# day11.py
…
def expand_dimension(
    galaxies: set,
    coords_to_expand: list[int],
    expansion_coeff: ExpansionCoeff,
) -> set:
    dimension = "x" if expansion_coeff.y == 0 else "y"
    for coord in reversed(coords_to_expand):
        new_galaxies = set()
        for galaxy in galaxies:
            if getattr(galaxy, dimension) >= coord:
                galaxy = Galaxy.expand(galaxy, *expansion_coeff)
            new_galaxies.add(galaxy)
        galaxies = new_galaxies
    return new_galaxies
```

The `expand_dimension()` function may not be so straightforward, so let us walk through it line by line. We start by getting the dimension that we are supposed to expand on by inspecting the `expansion_coeff` object. If its `y` attribute is `0`, we are expanding on the `x` dimension and, conversely, if the `x` attribute is `0`, we are expanding on the `y` dimension.

We then enter a nested loop. The outer part of it runs through all the coordinates that we need to expand. We loop through them in reverse order so we don't move galaxies past coordinates that we have not yet considered, which could result in moving a galaxy more than it should have been.

Before entering the inner loop, we create a set, `new_galaxies`, which will contain all the galaxies after the current coordinate has been used. Some of the new galaxies might be shifted, while others might not.

After the inner loop has terminated, we assign `galaxies` to be `new_galaxies`, and move on to the next coordinate to expand. At the end of this process, all galaxies will have been shifted appropriately.

And that is it. All we need to do now is to call the solver with the correct coefficient:

```
# day11.py
print(solve(universe, coeff=2))
```

This will give us the solution for part one.

Part two — problem statement

As with the first problem, part two is just a slight variation of part one. Let us see the problem statement:

"Now, instead of the expansion you did before, make each empty row or column one million times larger. That is, each empty row should be replaced with 1,000,000 empty rows, and each empty column should be replaced with 1,000,000 empty columns.

(In the example above, if each empty row or column were merely 100 times larger, the sum of the shortest paths between every pair of galaxies would be 8,410. However, your universe will need to expand far beyond these values.)

Starting with the same initial image, expand the universe according to these new rules, then find the length of the shortest path between every pair of galaxies. What is the sum of these lengths?"

Quite often, in Advent of Code, part two is where we realize whether the implementation of part one is good enough. In this case, because we have chosen to represent galaxies using a set of `Galaxy` objects, rather than sticking with a list of strings (or a list of lists), we will not have to change anything in our code, other than the expansion coefficient we pass the `solve()` function.

Part two — solution

Let us see how we call `solve()` for the second part:

```
# day11.py
print(solve(universe, coeff=int(1e6)))
```

And that is it. Now, we pass 1,000,000, instead of 2, and we get the correct result for part two.

The key takeaway is that, by choosing the right data structure in part one, we can expand the universe by any coefficient without incurring any penalty.

The technique we used is a version of a concept called **Sparse Matrix**, or **Sparse Array**. You can learn about it at `https://en.wikipedia.org/wiki/Sparse_matrix`.

When dealing with data in the form of a matrix, normally the data structure we would use is a list of lists (or, as in the case of this problem, a list of strings). However, sometimes the matrix is mostly empty, and the important data is just a small fraction of the whole.

In the problem's universe, for example, galaxies are just a small portion of the whole universe, which is otherwise empty. It is, therefore, appropriate to represent them not by using a list of lists (or a list of strings) but by choosing a different data structure. Here, we have chosen a set of coordinates because it suffices to retain all the information we need.

In other scenarios, a dictionary might have been necessary. Say, for example, that each galaxy had a luminosity factor associated with it. Using a dictionary, we could have represented each galaxy by setting coordinates as keys, and luminosity factors as values. The main point would still be the same: we would only be storing the galaxy data, but none of the empty space that we would have had to store if we were using a list of lists.

As we mentioned in earlier chapters, choosing the right data structures is of paramount importance. In this problem, had we chosen to create an expanded version of the universe by storing it in another list of strings (or a list of lists), it would have been fine for part one, but not so for part two.

Final considerations

Before we end this chapter, here are some final considerations.

First of all, as mentioned at the beginning of this chapter, the solutions to the two problems we presented do not claim to be the most elegant, nor the most efficient. There are faster algorithms we could have written that would perform much better on inputs of larger size.

Moreover, the way in which we structured the code, using OOP for *Camel Cards* and a functional approach for *Cosmic Expansion*, was just to make sure we could show you different ways of structuring code to solve a given problem.

Furthermore, we could have chosen other ways to split the solutions into classes and functions, and we could have also used different data structures to represent the data.

We have tried to prioritize readability and simplicity, overall, while still offering you a peek into concepts we have not been able to explore in the rest of the book, such as the use of custom comparator functions, or sparse matrixes.

We hope you have enjoyed this brief detour from *professional Python*, and we also hope to have sparked some curiosity in you.

Our advice is to sign up to Advent of Code, and at least try to come up with your own solutions for the problems in this chapter. Try to use OOP where we did not, and vice versa. Try to use different algorithms and other ways to structure the data. Most of all, have fun. Solving programming challenges can be lots of fun and, if you are like us, quite addictive!

We end this chapter with a list of programming challenge websites that we hope you will find interesting.

Other programming challenge websites

Here is a list of some of our favorite challenge websites. Some of them are free, some are not. Some are math oriented, while others are more focused on pure programming. Some help with interview preparation, while others are just for fun.

Interview preparation:

- LeetCode: `https://leetcode.com/`
- HackerRank: `https://www.hackerrank.com/`
- CodeSignal: `https://codesignal.com/`
- Coderbyte: `https://coderbyte.com/`
- HackerEarth: `https://www.hackerearth.com/`

Competitive programming:

- Codeforces: `https://codeforces.com/`
- Topcoder: `https://www.topcoder.com/`
- AtCoder: `https://atcoder.jp/`
- Sphere Online Judge (SPOJ): `https://www.spoj.com/`

Skill building and learning:

- Project Euler: `https://projecteuler.net/` (*Fabrizio used to be a member of Project Euler's dev team. He created some problems and collaborated on others*)
- Exercism: `https://exercism.org/`
- Codewars: `https://www.codewars.com/`

Fun and community:

- Advent of Code: `https://adventofcode.com/`
- CodinGame: `https://www.codingame.com/`

Machine learning:

- Kaggle: `https://www.kaggle.com/`

We hope you will take some time to explore a few of them; they will help you keep your mind sharp and brush up, or learn, algorithms, data structures, and new languages.

Summary

In this chapter, we have explored the world of programming challenges. We have solved two problems from the Advent of Code website and learned a little bit about a different universe in which programming is used for learning, fun, preparing for interviews, and competitions.

We also learned about custom comparator functions and sparse matrixes, and saw how some of the concepts we learned in previous chapters can be applied to solve a problem.

Now, our journey together has come to an end. It is up to you to keep the momentum up and make the most of what you learned in these pages. We tried to equip you with a solid foundation that should be enough to support you while you take the next steps, both in terms of knowledge and in terms of methodologies.

We hope to have been successful in conveying our passion and experience to you, and trust that it will accompany you wherever you go from here.

We hope you enjoyed reading this book, and best of luck!

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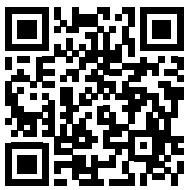

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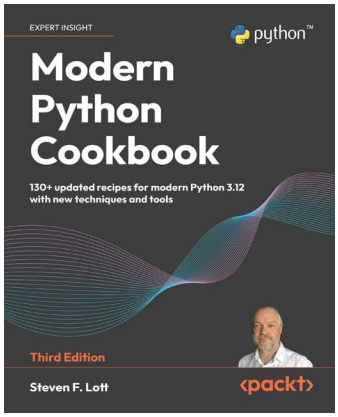

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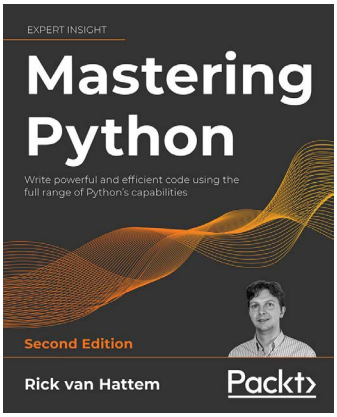

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