

Pandas IN ACTION

Boris Paskhaver



MANNING

Pandas in Action

BORIS PASKHAVER



MANNING
SHELTER ISLAND

For online information and ordering of this and other Manning books, please visit www.manning.com. The publisher offers discounts on this book when ordered in quantity. For more information, please contact

Special Sales Department
Manning Publications Co.
20 Baldwin Road
PO Box 761
Shelter Island, NY 11964
Email: orders@manning.com

©2021 by Manning Publications Co. All rights reserved.

No part of this publication may be reproduced, stored in a retrieval system, or transmitted, in any form or by means electronic, mechanical, photocopying, or otherwise, without prior written permission of the publisher.

Many of the designations used by manufacturers and sellers to distinguish their products are claimed as trademarks. Where those designations appear in the book, and Manning Publications was aware of a trademark claim, the designations have been printed in initial caps or all caps.

- ⊗ Recognizing the importance of preserving what has been written, it is Manning's policy to have the books we publish printed on acid-free paper, and we exert our best efforts to that end. Recognizing also our responsibility to conserve the resources of our planet, Manning books are printed on paper that is at least 15 percent recycled and processed without the use of elemental chlorine.



Manning Publications Co.
20 Baldwin Road
PO Box 761
Shelter Island, NY 11964

Development editor: Sarah Miller
Technical development editor: Al Krinker
Review editor: Aleks Dragosavljević
Production editor: Deirdre S. Hiam
Copyeditor: Keir Simpson
Proofreader: Jason Everett
Technical proofreader: Mathijs Affourtit
Typesetter and cover designer: Marija Tudor

ISBN 9781617297434

Printed in the United States of America

contents

preface *xiii*
acknowledgments *xv*
about this book *xvii*
about the author *xx*
about the cover illustration *xxi*

PART 1 CORE PANDAS 1

1 *Introducing pandas* 3

- 1.1 Data in the 21st century 4
- 1.2 Introducing pandas 4
 - Pandas vs. graphical spreadsheet applications* 6 □ *Pandas vs. its competitors* 8
- 1.3 A tour of pandas 9
 - Importing a data set* 9 □ *Manipulating a DataFrame* 11
 - Counting values in a Series* 14 □ *Filtering a column by one or more criteria* 15 □ *Grouping data* 18

2 *The Series object* 22

- 2.1 Overview of a Series 23
 - Classes and instances* 24 □ *Populating the Series with values* 24
 - Customizing the Series index* 26 □ *Creating a Series with missing values* 29

| | | |
|-----|---|----|
| 2.2 | Creating a Series from Python objects | 30 |
| 2.3 | Series attributes | 32 |
| 2.4 | Retrieving the first and last rows | 34 |
| 2.5 | Mathematical operations | 36 |
| | <i>Statistical operations</i> | 36 |
| | <i>Arithmetic operations</i> | 43 |
| | <i>Broadcasting</i> | 45 |
| 2.6 | Passing the Series to Python’s built-in functions | 48 |
| 2.7 | Coding challenge | 50 |
| | <i>Problems</i> | 50 |
| | <i>Solutions</i> | 50 |

3 Series methods 54

| | | |
|-----|---|----|
| 3.1 | Importing a data set with the <code>read_csv</code> function | 55 |
| 3.2 | Sorting a Series | 60 |
| | <i>Sorting by values with the <code>sort_values</code> method</i> | 60 |
| | <i>Sorting by index with the <code>sort_index</code> method</i> | 62 |
| | <i>Retrieving the smallest and largest values with the <code>nsmallest</code> and <code>nlargest</code> methods</i> | 64 |
| 3.3 | Overwriting a Series with the <code>inplace</code> parameter | 65 |
| 3.4 | Counting values with the <code>value_counts</code> method | 66 |
| 3.5 | Invoking a function on every Series value with the <code>apply</code> method | 72 |
| 3.6 | Coding challenge | 75 |
| | <i>Problems</i> | 75 |
| | <i>Solutions</i> | 76 |

4 The DataFrame object 79

| | | |
|-----|--|----|
| 4.1 | Overview of a DataFrame | 80 |
| | <i>Creating a DataFrame from a dictionary</i> | 80 |
| | <i>Creating a DataFrame from a NumPy ndarray</i> | 81 |
| 4.2 | Similarities between Series and DataFrames | 83 |
| | <i>Importing a DataFrame with the <code>read_csv</code> function</i> | 83 |
| | <i>Shared and exclusive attributes of Series and DataFrames</i> | 84 |
| | <i>Shared methods of Series and DataFrames</i> | 87 |
| 4.3 | Sorting a DataFrame | 90 |
| | <i>Sorting by a single column</i> | 90 |
| | <i>Sorting by multiple columns</i> | 92 |
| 4.4 | Sorting by index | 94 |
| | <i>Sorting by row index</i> | 94 |
| | <i>Sorting by column index</i> | 95 |
| 4.5 | Setting a new index | 95 |

| | | |
|------|--|-----|
| 4.6 | Selecting columns and rows from a DataFrame | 96 |
| | <i>Selecting a single column from a DataFrame</i> | 96 |
| | <i>Selecting multiple columns from a DataFrame</i> | 97 |
| 4.7 | Selecting rows from a DataFrame | 99 |
| | <i>Extracting rows by index label</i> | 99 |
| | <i>Extracting rows by index position</i> | 101 |
| | <i>Extracting values from specific columns</i> | 103 |
| 4.8 | Extracting values from Series | 106 |
| 4.9 | Renaming columns or rows | 106 |
| 4.10 | Resetting an index | 108 |
| 4.11 | Coding challenge | 109 |
| | <i>Problems</i> | 109 |
| | <i>Solutions</i> | 109 |

5 Filtering a DataFrame 113

| | | |
|-----|---|-----|
| 5.1 | Optimizing a data set for memory use | 114 |
| | <i>Converting data types with the astype method</i> | 116 |
| 5.2 | Filtering by a single condition | 120 |
| 5.3 | Filtering by multiple conditions | 124 |
| | <i>The AND condition</i> | 124 |
| | <i>The OR condition</i> | 125 |
| | <i>Inversion with ~</i> | 126 |
| | <i>Methods for Booleans</i> | 127 |
| 5.4 | Filtering by condition | 127 |
| | <i>The isin method</i> | 127 |
| | <i>The between method</i> | 128 |
| | <i>The isnull and notnull methods</i> | 130 |
| | <i>Dealing with null values</i> | 132 |
| 5.5 | Dealing with duplicates | 134 |
| | <i>The duplicated method</i> | 134 |
| | <i>The drop_duplicates method</i> | 136 |
| 5.6 | Coding challenge | 139 |
| | <i>Problems</i> | 139 |
| | <i>Solutions</i> | 140 |

PART 2 APPLIED PANDAS 145

6 Working with text data 147

| | | |
|-----|--|-----|
| 6.1 | Letter casing and whitespace | 148 |
| 6.2 | String slicing | 151 |
| 6.3 | String slicing and character replacement | 153 |
| 6.4 | Boolean methods | 155 |

- 6.5 Splitting strings 157
- 6.6 Coding challenge 162
 - Problems* 162 ▪ *Solutions* 162
- 6.7 A note on regular expressions 163

7 *MultiIndex DataFrames* 165

- 7.1 The MultiIndex object 166
- 7.2 MultiIndex DataFrames 170
- 7.3 Sorting a MultiIndex 175
- 7.4 Selecting with a MultiIndex 179
 - Extracting one or more columns* 179 ▪ *Extracting one or more rows with loc* 182 ▪ *Extracting one or more rows with iloc* 186
- 7.5 Cross-sections 188
- 7.6 Manipulating the Index 189
 - Resetting the index* 189 ▪ *Setting the index* 193
- 7.7 Coding challenge 194
 - Problems* 194 ▪ *Solutions* 195

8 *Reshaping and pivoting* 198

- 8.1 Wide vs. narrow data 199
- 8.2 Creating a pivot table from a DataFrame 200
 - The pivot_table method* 201 ▪ *Additional options for pivot tables* 205
- 8.3 Stacking and unstacking index levels 207
- 8.4 Melting a data set 209
- 8.5 Exploding a list of values 213
- 8.6 Coding challenge 214
 - Problems* 214 ▪ *Solutions* 215

9 *The GroupBy object* 220

- 9.1 Creating a GroupBy object from scratch 221
- 9.2 Creating a GroupBy object from a data set 222
- 9.3 Attributes and methods of a GroupBy object 225
- 9.4 Aggregate operations 229
- 9.5 Applying a custom operation to all groups 232
- 9.6 Grouping by multiple columns 233

- 9.7 Coding challenge 235
Problems 235 ▪ *Solutions* 235

10 *Merging, joining, and concatenating* 239

- 10.1 Introducing the data sets 241
10.2 Concatenating data sets 243
10.3 Missing values in concatenated DataFrames 245
10.4 Left joins 247
10.5 Inner joins 249
10.6 Outer joins 251
10.7 Merging on index labels 253
10.8 Coding challenge 254
Problems 256 ▪ *Solutions* 256

11 *Working with dates and times* 260

- 11.1 Introducing the Timestamp object 261
How Python works with datetimes 261 ▪ *How pandas works with datetimes* 264
11.2 Storing multiple timestamps in a DatetimeIndex 266
11.3 Converting column or index values to datetimes 268
11.4 Using the DatetimeProperties object 269
11.5 Adding and subtracting durations of time 273
11.6 Date offsets 275
11.7 The Timedelta object 277
11.8 Coding challenge 282
Problems 282 ▪ *Solutions* 283

12 *Imports and exports* 289

- 12.1 Reading from and writing to JSON files 290
Loading a JSON file Into a DataFrame 292 ▪ *Exporting a DataFrame to a JSON file* 298
12.2 Reading from and writing to CSV files 299
12.3 Reading from and writing to Excel workbooks 301
Installing the xlrd and openpyxl libraries in an Anaconda environment 301 ▪ *Importing Excel workbooks* 302
Exporting Excel workbooks 305

12.4 Coding challenge 306
Problems 307 • *Solutions* 307

13 Configuring pandas 310

13.1 Getting and setting pandas options 311
13.2 Precision 315
13.3 Maximum column width 316
13.4 Chop threshold 316
13.5 Option context 317

14 Visualization 319

14.1 Installing matplotlib 320
14.2 Line charts 320
14.3 Bar graphs 325
14.4 Pie charts 327

appendix A Installation and setup 329

appendix B Python crash course 347

appendix C NumPy crash course 383

appendix D Generating fake data with Faker 391

appendix E Regular expressions 397

index 409

****preface****

Truth be told, I discovered pandas entirely by luck.

In 2015, I interviewed for a data operations analyst position at Indeed.com, the world’s largest jobs site. For my final technical challenge, I was asked to derive insights from an internal data set, using the Microsoft Excel spreadsheet software. Eager to impress, I pulled out as many tricks as I could from my data analysis toolbox: column sorts, text manipulations, pivot tables, and of course the iconic VLOOKUP function. (OK, maybe *iconic* is a bit of an exaggeration.)

Strange as it may sound, at the time I didn’t realize that there were any tools for data analysis besides Excel. Excel was ubiquitous: my parents used it, my teachers used it, and my colleagues used it. It felt like an established standard. So when I received a job offer, I immediately bought about \$100 worth of Excel books and started studying. It was time to become a spreadsheet specialist!

I showed up for my first day of work with a printout of the 50 most-used Excel functions. Barely after I finished logging into my work computer, my manager pulled me into a conference room and informed me that priorities had shifted. The team’s data sets had ballooned to a size that Excel could no longer support. My teammates were also looking for ways to automate the redundant steps in their daily and weekly reports. Luckily, my manager had figured out a solution to both problems. He asked me whether I’d heard of pandas.

“The furry animal?” I asked, perplexed.

“No,” he said. “The Python data analysis library.”

After all my prep, it was time to learn a new technology from scratch. I was a little nervous; I’d never written a line of code before. I was an Excel guy, wasn’t I? Was I capable of doing this? There was only one way to find out. I started diving into the offi-

cial pandas documentation, into YouTube videos, books, workshops, Stack Overflow questions, and whatever data sets I could get my hands on. I was relieved to discover how easy and joyful it was to get started with pandas. The code felt intuitive and straightforward. The library was fast. The features were well-developed and expansive. With pandas, I could accomplish a lot of data manipulation with a little code.

Stories like mine are common in the Python community. The language's astronomical growth over the past decade is often attributed to the ease with which new developers can pick it up. I am confident that if you're in a position similar to mine, you can learn pandas just as well. If you're looking to expand your data analysis skills beyond Excel spreadsheets, this book is your invitation.

When I felt comfortable with pandas, I continued to explore Python and then other programming languages. In many ways, pandas spearheaded my transition into full-time software engineering. I owe a lot to this powerful library, and I'm excited to pass on the torch of knowledge to you. I hope that you discover the magic of what code can do for you.

acknowledgments

It took a lot to get *Pandas in Action* to the finish line, and I want to express my utmost gratitude to the people who supported me in its two-year writing process.

First and foremost, a warm thank you to my wonderful girlfriend, Meredith. From the first sentence, she was steadfast in her support. She's a vivacious, funny, and kind soul who always picked me up when the going got tough. This book is better because of her. Thank you, Merbear.

Thank you to my parents, Irina and Dmitriy, for providing a welcoming home where I can always find respite.

Thank you to my twin sisters, Mary and Alexandra. They're remarkably clever, inquisitive, and hard-working for their age, and I couldn't be prouder of them. Good luck at college!

Thanks to Watson, our golden retriever. He's not much of a Python expert, but he makes up for it with his entertaining and friendly demeanor.

A big thank you to my editor, Sarah Miller, who was an absolute joy to work with. I am grateful for her patience and insights throughout the process. She was the true captain of the ship, and she kept everything sailing smoothly.

I would not be a software engineer without the opportunities I was given at Indeed. I want to offer my former manager, Srdjan Bodruzic, a hearty thank you for his generosity and mentorship (and for hiring me!). Thanks to my CX teammates—Tommy Winschel, Danny Moncada, JP Schultz, and Travis Wright—for their wisdom and humor. Thanks to other Indeedians who offered a helping hand during my tenure: Matthew Morin, Chris Hatton, Chip Borsi, Nicole Saglimbene, Danielle Scoli, Blairr Swayne, and George Improglou. Thanks to anybody I've shared a dinner with at Sophie's Cuban Cuisine!

I started writing this book as a software engineer at Stride Consulting. I want to thank many Striders for their support throughout the process: David “The Dominator” DiPanfilo, Min Kwak, Ben Blair, Kirsten Nordine, Michael “Bobby” Nunez, Jay Lee, James Yoo, Ray Veliz, Nathan Riemer, Julia Berchem, Dan Plain, Nick Char, Grant Ziolkowski, Melissa Wahnish, Dave Anderson, Chris Aporta, Michael Carlson, John Galioto, Sean Marzug-McCarthy, Travis Vander Hoop, Steve Solomon, and Jan Mlčoch.

Thank you to the friendly faces I’ve had the opportunity to work with as a software engineer and consultant: Francis Hwang, Inhak Kim, Liana Lim, Matt Bambach, Brenton Morris, Ian McNally, Josh Philips, Artem Kochnev, Andrew Kang, Andrew Fader, Karl Smith, Bradley Whitwell, Brad Popolek, Eddie Wharton, Jen Kwok, and my favorite coffee crew: Adam McAmis and Andy Fritz.

Thank you to the following people for all they add to my life: Nick Bianco, Cam Stier, Keith David, Michael Cheung, Thomas Philippeau, Nicole DiAndrea, and James Rokeach.

Thanks to my favorite band, New Found Glory, for providing the soundtrack to many writing sessions. Pop punk’s not dead!

Thank you to the Manning staff who shepherded the project to completion and helped with marketing efforts: Jennifer Houle, Aleksandar Dragosavljević, Radmila Ercegovac, Candace Gillhoolley, Stjepan Jureković, and Lucas Weber. Thanks also to the Manning staff who oversaw the content: Sarah Miller, my developmental editor; Deirdre Hiam, my product manager; Keir Simpson, my copyeditor; and Jason Everett, my proofreader.

Thanks to the technical reviewers who helped me iron out the kinks: Al Pezewski, Alberto Ciarlanti, Ben McNamara, Björn Neuhaus, Christopher Kottmyer, Dan Sheikh, Dragos Manailouiu, Erico Lendzian, Jeff Smith, Jérôme Bâton, Joaquin Beltran, Jonathan Sharley, Jose Apablaza, Ken W. Alger, Martin Czygan, Mathijs Affourtit, Matthias Busch, Mike Cuddy, Monica E. Guimaraes, Ninoslav Cerkez, Rick Prins, Syed Hasany, Viton Vitanis, and Vybhavreddy Kammireddy Changalreddy. I am a better writer and educator thanks to your efforts.

Finally, to the city of Hoboken, my home for the past six years. I wrote many parts of this manuscript in its public library, local cafes, and bubble tea shops. I made many forward strides in my life in this town, and it is forever etched into my history. Thank you, Hoboken!

about this book

Who should read this book

Pandas in Action is a comprehensive introduction to the pandas library for data analysis. Pandas enables you to perform a multitude of data manipulations with ease: sorting, joining, pivoting, cleaning, deduping, aggregating, and more. The book approaches the subject matter incrementally. It introduces pandas one piece at a time, starting with its smaller building blocks and proceeding to its larger data structures.

Pandas in Action is written for data analysts who have intermediate experience with spreadsheet software (such as Microsoft Excel, Google Sheets, and Apple Numbers) and/or alternative data analysis tools (such as R and SAS). It is also a fitting title for Python developers who are curious to learn more about data analysis.

How this book is organized: A road map

Pandas in Action consists of 14 chapters spread across two parts.

Part 1, “Core pandas,” introduces the base mechanics of the pandas library in an incremental manner:

- Chapter 1 analyzes a sample dataset with pandas to present a big-picture overview of what the library is capable of.
- Chapter 2 introduces the `Series` object, a core pandas data structure that stores a collection of ordered data.
- Chapter 3 dives into the `Series` object in greater depth. We explore various `Series` operations, including sorting values, dropping duplicates, extracting minimums and maximums, and more.
- Chapter 4 introduces the `DataFrame`, a two-dimensional table of data. We apply concepts from the previous chapters to the new data structure and introduce additional manipulations.

- Chapter 5 shows you how to filter subsets of rows from a DataFrame by using various logical conditions: equality, inequality, comparison, inclusion, exclusion, and more.

Part 2, “Applied pandas,” focuses on more-advanced pandas features and the problems they solve in real-world datasets:

- Chapter 6 teaches you how to work with imperfect text data in pandas. We discuss how to solve issues such as removing whitespace, fixing character casing, and extracting multiple values from a single column.
- Chapter 7 discusses the MultiIndex, which allows us to combine multiple column values into a single identifier for a row of data.
- Chapter 8 describes how to aggregate our data in a pivot table, shift headers from the row axis to the column axis, and convert our data from wide format to narrow format.
- Chapter 9 explores how to group rows into buckets and aggregate the resulting collections via the GroupBy object.
- Chapter 10 walks you through combining multiple data sets into a single one by using various joins.
- Chapter 11 demonstrates how to work with dates and times in pandas. It covers topics such as sorting dates, calculating durations, and determining whether a date falls at the start of a month or quarter.
- Chapter 12 shows you how to import additional file types into pandas, including Excel and JSON. We also learn how to export data from pandas.
- Chapter 13 focuses on configuring the library’s settings. We dive into how to modify the number of displayed rows, alter the precision of floating-point numbers, round values below a threshold, and more.
- Chapter 14 explores data visualization using the matplotlib library. We see how to use pandas data to create line charts, bar graphs, pie charts, and more.

Each chapter builds upon the preceding one. For those who are learning pandas from scratch, I recommend proceeding through the chapters in linear order. Simultaneously, to ensure that the book is helpful as a reference guide, I’ve written each chapter as an independent tutorial with its own data sets. We start writing our code from scratch at the beginning of each chapter, so you can start with any chapter you like.

Most chapters conclude with a coding challenge that allows you to practice its concepts. I strongly recommend taking a shot at these exercises.

Pandas is built on the Python programming language, and basic knowledge of the language’s mechanics is recommended before you get started. For those who have limited experience in Python, appendix B offers a hearty introduction to the language.

About the code

This book contains many examples of source code, which is formatted in a fixed-width font like `this` to separate it from ordinary text.

The source code for the book’s examples is available at the following GitHub repository: <https://github.com/paskhaver/pandas-in-action>. For those who are new to Git and GitHub, look for a Download Zip button on the repository page. Those who are experienced with Git and GitHub are welcome to clone the repo from the command line.

The repository also includes the complete data sets for the text. When I was learning pandas, one of my biggest frustrations was that tutorials loved to rely on randomly generated data. There was no consistency, no context, no story, no fun. In this book, we’ll work with many real-world data sets that cover everything from basketball players’ salaries to Pokémon types to restaurant health inspections. Data is everywhere around us, and pandas is one of the best tools available today to make sense of it. I hope that you enjoy the casual focus of the data sets.

liveBook discussion forum

Purchase of *Pandas in Action* includes free access to a private web forum run by Manning Publications where you can make comments about the book, ask technical questions, and receive help from the author and from other users. To access the forum, go to <https://livebook.manning.com/#!/book/pandas-in-action/discussion>. You can also learn more about Manning’s forums and the rules of conduct at <https://livebook.manning.com/#!/discussion>.

Manning’s commitment to our readers is to provide a venue where meaningful dialogue between individual readers and between readers and the author can take place. It is not a commitment to any specific amount of participation on the part of the author, whose contribution to the forum remains voluntary (and unpaid). We suggest that you try asking the author some challenging questions lest their interest stray! The forum and the archives of previous discussions will be accessible from the publisher’s website as long as the book is in print.

Other online resources

- The official pandas documentation is available at <https://pandas.pydata.org/docs>.
- In my spare time, I create technical video courses on Udemy. You can find the courses at <https://www.udemy.com/user/boris-paskhaver>; they include a 20-hour pandas course and a 60-hour Python course.
- Feel free to reach out to me via Twitter (<https://twitter.com/boris-paskhaver>) or LinkedIn (<https://www.linkedin.com/in/boris-paskhaver>).

about the author

BORIS PASKHAVER is a full-stack software engineer, consultant, and online educator based in New York City. He has six courses on the e-learning platform Udemy with over 140 hours of videos, 300,000 students, 20,000 reviews, and 1 million minutes of content consumed monthly. Before becoming a software engineer, Boris worked as a data analyst and systems administrator. He graduated from New York University in 2013 with a double major in business economics and marketing.

about the cover illustration

The figure on the cover of *Pandas in Action* is captioned “Dame de Calais,” or Lady from Calais. The illustration is taken from a collection of dress costumes from various countries by Jacques Grasset de Saint-Sauveur (1757–1810), titled *Costumes de Différents Pays*, published in France in 1797. Each illustration is finely drawn and colored by hand. The rich variety of Grasset de Saint-Sauveur’s collection reminds us vividly of how culturally apart the world’s towns and regions were only 200 years ago. Isolated from one another, people spoke different dialects and languages. In the streets or in the countryside, it was easy to identify by their dress alone where they lived and what their trade or station in life was.

The way we dress has changed since then, and diversity by region, so abundant at the time, has faded away. Now it is hard to tell apart the inhabitants of different continents, let alone different towns, regions, or countries. Perhaps we have traded cultural diversity for a more varied personal life—certainly for a more varied and fast-paced technological life.

At a time when it is hard to tell one computer book from another, Manning celebrates the inventiveness and initiative of the computer business with book covers based on the deep diversity of regional life of two centuries ago, brought back to life by Grasset de Saint-Sauveur’s pictures.

Part 1

Core pandas

Welcome! In this section, we'll familiarize ourselves with the core mechanics of pandas and its two primary data structures: the one-dimensional Series and the two-dimensional DataFrame. Chapter 1 begins with an analysis of a data set with pandas so you can immediately get a sense of what is possible with the library. From there, we proceed to an in-depth exploration of the Series in chapters 2 and 3. We learn how to create a Series from scratch; import it from an external data set; and apply a slew of mathematical, statistical, and logical operations to it. In chapter 4, we introduce the tabular DataFrame and various ways to extract rows, columns, and values from its data. Finally, chapter 5 focuses on extracting subsets of DataFrame rows by applying logical criteria. Along the way, we'll work through eight datasets that cover everything from box-office grosses to NBA players to Pokémon.

This part covers the essentials of pandas, the fundamentals you need to know to work effectively with the library. I've made every effort to start from square one, from the smallest building blocks possible, and proceed to the larger and more complex elements. The following five chapters build the foundation for your mastery of pandas. Good luck!

Introducing pandas



This chapter covers

- The growth of data science in the 21st century
- The history of the pandas library for data analysis
- The pros and cons of pandas and its competitors
- Data analysis in Excel versus data analysis with a programming language
- A tour of the library's features through a working example

Welcome to *Pandas in Action!* Pandas is a library for data analysis built on top of the Python programming language. A *library* (also called a *package*) is a collection of code for solving problems in a specific field of endeavor. Pandas is a toolbox for data manipulation operations: sorting, filtering, cleaning, deduping, aggregating, pivoting, and more. The epicenter of Python’s vast data science ecosystem, pandas pairs well with other libraries for statistics, natural language processing, machine learning, data visualization, and more.

In this introductory chapter, we’ll explore the history and evolution of modern data analytics tools. We’ll see how pandas grew from one financial analyst’s pet

project to an industry standard used by companies such as Stripe, Google, and J.P. Morgan. We'll compare the library with its competitors, including Excel and R. We'll discuss the differences between working with a programming language and working with a graphical spreadsheet application. Finally, we'll use pandas to analyze a real-world data set. Consider this chapter to be a sneak preview of the concepts you'll master throughout the book. Let's dive in!

1.1 Data in the 21st century

"It is a capital mistake to theorize before one has data," Sherlock Holmes advises his assistant John Watson in "A Scandal in Bohemia," the first of Sir Arthur Conan Doyle's classic short stories pairing the duo. "Insensibly one begins to twist facts to suit theories, instead of theories to suit facts."

The wise detective's words continue to ring true more than a century after the publication of Doyle's work, in a world in which data is becoming increasingly prevalent in every facet of our lives. "The world's most valuable resource is no longer oil, but data," declared *The Economist* in a 2017 opinion piece. Data is *evidence*, and evidence is critical to businesses, governments, institutions, and individuals solving increasingly complex problems in our interconnected world. Across a breadth of industries, the world's most successful companies, from Facebook to Amazon to Netflix, cite data as the most prized asset in their portfolios. United Nations Secretary-General António Guterres called accurate data "the lifeblood of good policy and decision-making." Data powers everything from movie recommendations to medical treatments, from supply chain logistics to poverty-reduction initiatives. The success of communities, companies, and even countries in the 21st century will depend on their ability to acquire, aggregate, and analyze data.

1.2 Introducing pandas

The technological ecosystem of tools for working with data has grown tremendously over the past decade. Today, the open source pandas library is one of the most popular solutions available for data analysis and manipulation. *Open source* means that the library's source code is publicly available to download, use, modify, and distribute. Its license grants users more permissions than proprietary software such as Excel. Pandas is free to use. A global team of volunteer software developers maintains the library, and you can find its complete source code on GitHub (<https://github.com/pandas-dev/pandas>).

Pandas is comparable to Microsoft's Excel spreadsheet software and Google's in-browser Sheets application. In all three technologies, a user interacts with tables consisting of rows and columns of data. A row represents a record or, equivalently, one collection of values for the columns. Transformations are applied to coax the data into the desired state.

Figure 1.1 displays a sample transformation of a data set. The analyst applies an operation to the four-row data set on the left to arrive at the two-row data set on the

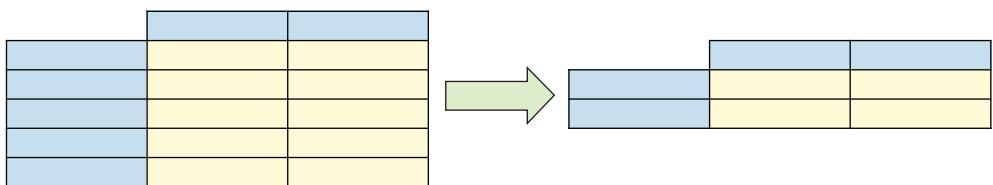


Figure 1.1 A sample transformation of a tabular data set

right. They may select rows that fit a criterion, for example, or remove duplicate rows from the original data set.

What makes pandas unique is the balance it strikes between processing power and user productivity. By relying on lower-level languages such as C for many of its calculations, the library can efficiently transform million-row data sets in milliseconds. At the same time, it maintains a simple and intuitive set of commands. It is easy to accomplish a lot with a little code in pandas.

Figure 1.2 shows some sample pandas code that imports and sorts a CSV data set. Don't worry about the code yet, but take a second to notice that the entire operation takes only two lines of code.

```
In [2]: populations = pd.read_csv("populations.csv")
populations.sort_values(by = "Population", ascending = False)

Out[2]:
      Country  Population
144        China  1433783686
  21        India  1366417754
156  United States  329064917
  76    Indonesia  270625568
147      Pakistan  216565318
  79       Brazil  211049527
   6       Nigeria  200963599
123    Bangladesh  163046161
```

Figure 1.2 A sample of code that imports and sorts a data set in pandas

Pandas works seamlessly with numbers, text, dates, times, missing data, and more. We'll explore its incredible versatility as we proceed through the more than 30 data sets included with this book.

The first version of pandas was developed in 2008 by software developer Wes McKinney, who was working at New York's AQR Capital Management investment firm. Dissatisfied with both Excel and the statistical programming language R, McKinney searched for a tool that would make it easy to solve common data problems in the

financial industry, particularly cleanup and aggregation. Unable to find an ideal product, he decided to build one himself. At the time, Python was far from the powerhouse it is today, but the beauty of the language inspired McKinney to build his library on top of its foundation. “I loved [Python] for its economy of expressions,” he stated in Quartz (<http://mng.bz/w0Na>). “You can express complicated ideas in Python with very little code, and it is very easy to read.”

Pandas has seen continual, extensive growth since its release to the public in December 2009. User counts are estimated to be between five and ten million.¹ As of June 2021, pandas has been downloaded more than 750 million times from PyPi, the centralized online repository of Python packages (<https://pepy.tech/project/pandas>). Its GitHub code repository has more than 30,000 stars (a star is equivalent to a “like” on the platform). Pandas questions make up a growing percentage of questions on the question-answer aggregator Stack Overflow, suggesting increased user interest.

I would argue that we can even credit pandas for the astronomical growth of Python itself. The language has exploded in popularity because of its prevalence in data science, a field to which pandas contributes greatly. Python is now the most common first language taught at colleges and universities. The TIOBE index, a ranking of programming language popularity by search engine traffic, declared Python to be the fastest-growing language of 2018.² “If Python can keep this pace, it will probably replace C and Java in 3 to 4 years’ time, thus becoming the most popular programming language of the world,” wrote TIOBE in a press release. As you learn pandas, you’ll also be learning Python, which is another perk of the library.

1.2.1 **Pandas vs. graphical spreadsheet applications**

Pandas requires a different mindset from a graphical spreadsheet app such as Excel. Programming is inherently more verbal than it is visual. We communicate with the computer through commands, not clicks. Because it makes fewer assumptions about what you’re trying to accomplish, a programming language tends to be more unforgiving. It needs to be *told* what to do with no uncertainty. We need to issue the correct instructions with the correct inputs in the correct order; otherwise, the program will not work.

Due to these stricter requirements, pandas has a steeper learning curve than Excel or Sheets. But if you have limited experience in Python or programming in general, there’s no need to worry! When you’re fiddling with functions such as SUMIF and VLOOKUP in Excel, you’re already thinking like a programmer. The process is the same: identify the correct function to use and then supply the right inputs in the proper order. Pandas requires an identical set of skills; the difference is that we’re communicating with the computer in a more verbose language.

¹ See “What’s the future of the pandas library?,” Data School, <https://www.dataschool.io/future-of-pandas>.

² See Oliver Peckham, “TIOBE Index: Python Reaches Another All-Time High,” HPC Wire, <http://mng.bz/w0XP>.

When you become familiar with its complexities, pandas grants you greater power and flexibility in your data manipulations. In addition to extending the range of your available procedures, programming allows you to automate them. You can write a piece of code once and reuse it across multiple files—perfect for those pesky daily and weekly reports. It's important to note that Excel comes bundled with Visual Basic for Applications (VBA), a programming language that also enables you to automate spreadsheet procedures. I would argue, however, that Python is easier to pick up than VBA and has uses beyond data analysis, making it a better investment of your time.

There are additional benefits to making the jump from Excel to Python. Jupyter Notebook, the coding environment often paired with pandas, allows for more dynamic, interactive, and comprehensive reports. A Jupyter Notebook consists of cells, each of which contains a chunk of executable code. An analyst can integrate these cells with headers, charts, descriptions, annotations, images, videos, diagrams, and more. Readers can follow the analyst's step-by-step logic to see how they reached their conclusion, not only their final result.

Another advantage of pandas is Python's large data science ecosystem. Pandas integrates easily with libraries for statistics, natural language processing, machine learning, web scraping, data visualization, and more. New libraries appear yearly. Experimentation is welcomed. Innovation is constant. These robust tools sometimes remain underdeveloped in corporate competitors, which lack the support of a large, global community of contributors.

Graphical spreadsheet applications also begin to struggle as data sets grow; pandas is significantly more powerful than Excel in this aspect. The capacity of the library is limited only by the computer's memory and processing power. On most modern machines, pandas plays well with multigigabyte data sets with millions of rows, especially when a developer knows how to exploit all its performance optimizations. In a blog post describing the limitations of the library, creator Wes McKinney wrote, "Nowadays, my rule of thumb for pandas is that you should have 5 to 10 times more RAM as the size of your data set" (<http://mng.bz/qeK6>).

Part of the challenge in choosing the best tool for the job is defining what terms such as *data analysis* and *big data* mean to your organization and your project. Excel, which is used by approximately 750 million working professionals globally, limits its spreadsheets to 1,048,576 rows of data.³ For some analysts, 1 million rows of data are more than any report requires; for others, 1 million rows only scratch the surface.

I would advise you to look at pandas as being not the best data analysis solution but a powerful option to use alongside other modern technologies. Excel is still an excellent choice for quick, easy data manipulations. A spreadsheet application usually makes assumptions about your intent, which is why it takes only a few clicks to import a CSV file or sort a column of 100 values. There's no real advantage to using pandas for simple tasks like these (although it's more than capable of doing them). But what

³ See Andy Patrizio, "Excel: Your entry into the world of data analytics," *Computer World*, <http://mng.bz/qe6r>.

do you use when you need to clean text values in two data sets of ten million rows each, remove their duplicate records, join them, and replicate that logic for 100 batches of files? For those scenarios, it's easier and less time-consuming to do the work with Python and pandas.

1.2.2 Pandas vs. its competitors

Data science enthusiasts frequently compare pandas with the open source programming language R and the proprietary software suite SAS. Each solution has its own community of advocates.

R is a specialized language with a foundation in statistics, whereas Python is a generalist language used in multiple technical domains. Predictably, the two languages tend to attract users with expertise in specific fields. Hadley Wickham, a prominent developer in the R community who built a collection of data science packages called tidyverse, advises users to see the two languages as collaborators rather than rivals. "These things exist independently and are both awesome in different ways," he said in *Quartz* (<http://mng.bz/Jv9V>). "A pattern that I see is that the data science team in a company uses R and the data engineering team uses Python. The Python people tend to have a background in software engineering and are very confident about their programming skills. . . . [The R users] really like R, but can't argue with the engineering team because they don't have the language to make that argument." One language may have an advanced feature that the other does not, but the two have achieved near parity when it comes to common tasks in data analysis. Developers and data scientists simply gravitate to what they know best.

A suite of complementary software tools that supports statistics, data mining, econometrics, and more, SAS is a commercial product developed by the North Carolina-based SAS Institute. It charges an annual user subscription fee that varies based on the bundle of selected software. The advantages conferred by a corporate-backed product include technical and visual consistency across tools, robust documentation, and a product road map geared towards enterprise clients' needs. Open source technology like pandas enjoys a more free-for-all approach; developers work for their needs and for other developers' needs, which sometimes miss market trends.

Certain technologies share features with pandas but serve intrinsically different purposes. SQL is one example. *SQL* (Structured Query Language) is a language for communicating with relational databases. A *relational database* consists of tables of data linked by common keys. We can use SQL for basic data manipulations such as extracting columns from tables and filtering rows by a criterion, but its functionalities are greater in scope and fundamentally revolve around data management. Databases are built to *store* data; data analysis is a secondary use case. SQL can create new tables, update existing records with new values, delete existing records, and so on. By comparison, pandas is built entirely for data analysis: statistical calculations, data wrangling, data merges, and more. In a typical work environment, the two tools often serve as complements. An analyst might use SQL to extract an initial cluster of data and then use pandas to manipulate it.

In summary, pandas is not the only tool in town, but it is a powerful, popular, and valuable solution for solving most data analysis problems. Again, Python truly shines in its focus on brevity and productivity. As its creator, Guido van Rossum, remarked, “The joy of coding Python should be in seeing short, concise, readable [data structures] that express a lot of action in a small amount of clear code” (<http://mng.bz/7jo7>). Pandas lives up to that standard and is an excellent next step for spreadsheet analysts who are eager to grow their programming skills with a powerful, modern data analysis toolkit.

1.3 A tour of pandas

The best way to grasp the power of pandas is to see it in action. Let’s take a quick tour of the library by analyzing a data set of the 700 highest-grossing movies of all time. I hope you are pleasantly surprised by how intuitive the syntax of pandas can be, even if you are new to programming.

As you proceed through the rest of the chapter, try not to overanalyze the code samples; you don’t even need to copy them. Our goal right now is to get a bird’s-eye view of the features and functionalities of pandas. Think about what the library can do; we’ll worry about how in greater detail later.

We’ll be using the Jupyter Notebook development environment to write our code throughout the book. If you need help setting up pandas and Jupyter Notebook on your computer, see appendix A. You can download all data sets and completed Jupyter Notebooks at <https://www.github.com/paskhaver/pandas-in-action>.

1.3.1 Importing a data set

Let’s get started! First, we’ll create a new Jupyter Notebook inside the same directory as the movies.csv file; then we’ll import the pandas library to gain access to its features:

```
In [1] import pandas as pd
```

The box to the left of the code (displaying the number 1 in the previous example) marks the cell’s execution order relative to the launch or restart of the Jupyter Notebook. You can execute the cells in any order, and you can execute the same cell multiple times.

As you read through the book, you are encouraged to experiment by executing different snippets of code in your Jupyter cells. Thus, it is OK if your execution numbers do not match those in the text.

Our data is stored in a single movies.csv file. A CSV (comma-separated values) file is a plain-text file that separates each row of data with a line break and each row value with a comma. The first row in the file holds the column headers for the data. Here’s a preview of the first three rows of movies.csv:

```
Rank,Title,Studio,Gross,Year
1,Avengers: Endgame,Buena Vista,"$2,796.30",2019
2,Avatar,Fox,"$2,789.70",2009
```

The first row lists the five columns in the data set: Rank, Title, Studio, Gross, and Year. The second row holds the first record or, equivalently, the data for the first movie. The film has a Rank of 1, a Title of "Avengers: Endgame", a Studio of "Buena Vista", a Gross of "\$2,796.30", and a Year of 2019. The next line holds the values for the next movie, and the pattern repeats for the remaining 750-plus rows in the data set.

Pandas can import various file types, each of which has an associated import function at the top level of the library. A *function* in pandas is equivalent to a function in Excel. It's a command that we issue, either to the library or an entity within it. In this scenario, we'll use the `read_csv` function to import the `movies.csv` file:

```
In [2] pd.read_csv("movies.csv")
```

```
Out [2]
```

| Rank | | Title | Studio | Gross | Year |
|------|-----|------------------------------|-----------------|------------|------|
| 0 | 1 | Avengers: Endgame | Buena Vista | \$2,796.30 | 2019 |
| 1 | 2 | Avatar | Fox | \$2,789.70 | 2009 |
| 2 | 3 | Titanic | Paramount | \$2,187.50 | 1997 |
| 3 | 4 | Star Wars: The Force Awakens | Buena Vista | \$2,068.20 | 2015 |
| 4 | 5 | Avengers: Infinity War | Buena Vista | \$2,048.40 | 2018 |
| ... | ... | ... | ... | ... | ... |
| 777 | 778 | Yogi Bear | Warner Brothers | \$201.60 | 2010 |
| 778 | 779 | Garfield: The Movie | Fox | \$200.80 | 2004 |
| 779 | 780 | Cats & Dogs | Warner Brothers | \$200.70 | 2001 |
| 780 | 781 | The Hunt for Red October | Paramount | \$200.50 | 1990 |
| 781 | 782 | Valkyrie | MGM | \$200.30 | 2008 |

```
782 rows × 5 columns
```

Pandas imports the CSV file's contents into an object called a `DataFrame`. Think of an object as a container for storing data. Different objects are optimized for different types of data, and we interact with them in different ways. Pandas uses one type of object (the `DataFrame`) to store multicolumn data sets and another type of object (the `Series`) to store single-column data sets. A `DataFrame` is comparable to a multicolumn table in Excel.

To avoid cluttering the screen, pandas displays only the first five and last five rows of the `DataFrame`. A row of ellipses (. . .) marks where the data gap occurs.

This `DataFrame` consists of five columns (Rank, Title, Studio, Gross, Year) and an index. The index is the range of ascending numbers on the left side of the `DataFrame`. Index labels serve as identifiers for rows of data. We can set any column as the index of the `DataFrame`. When we do not explicitly tell pandas which column to use, the library generates a numeric index starting from 0.

What column is a good candidate for the index? It's one whose values can act as a primary identifier or point of reference for each row. Among our five columns, Rank and Title are the two best options. Let's swap the autogenerated numeric index with the values from the Title column. We can do so directly during the CSV import:

```
In [3] pd.read_csv("movies.csv", index_col = "Title")
Out [3]
```

| Title | Rank | Studio | Gross | Year |
|------------------------------|------|-----------------|------------|------|
| Avengers: Endgame | 1 | Buena Vista | \$2,796.30 | 2019 |
| Avatar | 2 | Fox | \$2,789.70 | 2009 |
| Titanic | 3 | Paramount | \$2,187.50 | 1997 |
| Star Wars: The Force Awakens | 4 | Buena Vista | \$2,068.20 | 2015 |
| Avengers: Infinity War | 5 | Buena Vista | \$2,048.40 | 2018 |
| ... | ... | ... | ... | ... |
| Yogi Bear | 778 | Warner Brothers | \$201.60 | 2010 |
| Garfield: The Movie | 779 | Fox | \$200.80 | 2004 |
| Cats & Dogs | 780 | Warner Brothers | \$200.70 | 2001 |
| The Hunt for Red October | 781 | Paramount | \$200.50 | 1990 |
| Valkyrie | 782 | MGM | \$200.30 | 2008 |

782 rows × 4 columns

Next, we'll assign the DataFrame to a `movies` variable so that we can reference it elsewhere in our program. A *variable* is a user-assigned name for an object in the program:

```
In [4] movies = pd.read_csv("movies.csv", index_col = "Title")
```

For more on variables, check out appendix B.

1.3.2 Manipulating a DataFrame

We can look at the DataFrame from a variety of angles. We can extract a few rows from the beginning:

```
In [5] movies.head(4)
```

```
Out [5]
```

| Title | Rank | Studio | Gross | Year |
|------------------------------|------|-------------|------------|------|
| Avengers: Endgame | 1 | Buena Vista | \$2,796.30 | 2019 |
| Avatar | 2 | Fox | \$2,789.70 | 2009 |
| Titanic | 3 | Paramount | \$2,187.50 | 1997 |
| Star Wars: The Force Awakens | 4 | Buena Vista | \$2,068.20 | 2015 |

Or we can peek at the end of the data set instead:

```
In [6] movies.tail(6)
```

```
Out [6]
```

| Title | Rank | Studio | Gross | Year |
|--------------------------|------|-----------------|----------|------|
| 21 Jump Street | 777 | Sony | \$201.60 | 2012 |
| Yogi Bear | 778 | Warner Brothers | \$201.60 | 2010 |
| Garfield: The Movie | 779 | Fox | \$200.80 | 2004 |
| Cats & Dogs | 780 | Warner Brothers | \$200.70 | 2001 |
| The Hunt for Red October | 781 | Paramount | \$200.50 | 1990 |
| Valkyrie | 782 | MGM | \$200.30 | 2008 |

We can find out how many rows the DataFrame has:

```
In [7] len(movies)  
Out [7] 782
```

We can ask pandas for the number of rows and columns in the DataFrame. This data set has 782 rows and 4 columns:

```
In [8] movies.shape  
Out [8] (782, 4)
```

We can inquire about the total number of cells:

```
In [9] movies.size  
Out [9] 3128
```

We can ask for the data types of the four columns. In the following output, `int64` denotes an integer column, and `object` denotes a text column:

```
In [10] movies.dtypes  
Out [10]  
  
Rank        int64  
Studio      object  
Gross       object  
Year        int64  
dtype: object
```

We can extract a row from the data set by its numeric order in line, also called its index position. In most programming languages, the index starts counting at 0. Thus, if we wanted to pull out the 500th movie in the data set, we would target index position 499:

```
In [11] movies.iloc[499]  
Out [11] Rank          500  
        Studio        Fox  
        Gross        $288.30  
        Year         2018  
        Name: Maze Runner: The Death Cure, dtype: object
```

Pandas returns a new object here called a `Series`, a one-dimensional labeled array of values. Think of it as a single column of data with an identifier for each row. Notice that the `Series`' index labels (Rank, Studio, Gross, and Year) are the four columns from the `movies` DataFrame. Pandas has altered the presentation of the original row's values.

We can also use an index label to access a DataFrame row. As a reminder, our DataFrame index holds the films' titles. Let's extract the row values for everyone's favorite tearjerker, *Forrest Gump*. The next example extracts a row by its index label rather than its numeric position:

```
In [12] movies.loc["Forrest Gump"]

Out [12] Rank      119
         Studio    Paramount
         Gross     $677.90
         Year      1994
         Name: Forrest Gump, dtype: object
```

Index labels can contain duplicates. Two movies in the DataFrame have the title "101 Dalmatians", for example (the 1961 original and the 1996 remake):

```
In [13] movies.loc["101 Dalmatians"]

Out [13]
```

| Title | Rank | Studio | Gross | Year |
|----------------|------|-------------|----------|------|
| 101 Dalmatians | 425 | Buena Vista | \$320.70 | 1996 |
| 101 Dalmatians | 708 | Buena Vista | \$215.90 | 1961 |

Although pandas permits duplicates, I recommend keeping index labels unique if possible. A unique collection of labels accelerates the speed at which pandas can locate and extract a specific row.

The films in the CSV are sorted by values in the Rank column. What if we wanted to see the five movies with the most recent release date? We can sort the DataFrame by the values in another column, such as Year:

```
In [14] movies.sort_values(by = "Year", ascending = False).head()

Out [14]
```

| Title | Rank | Studio | Gross | Year |
|---------------------------------|------|------------------------|--------|------|
| Avengers: Endgame | 1 | Buena Vista | 2796.3 | 2019 |
| John Wick: Chapter 3 - Parab... | 458 | Lionsgate | 304.7 | 2019 |
| The Wandering Earth | 114 | China Film Corporation | 699.8 | 2019 |
| Toy Story 4 | 198 | Buena Vista | 519.8 | 2019 |
| How to Train Your Dragon: Th... | 199 | Universal | 519.8 | 2019 |

We can also sort DataFrames by values across multiple columns. Let's sort movies first by the Studio column's values and then by the Year column's values. Now we can see the films organized alphabetically by both studio and release date:

```
In [15] movies.sort_values(by = ["Studio", "Year"]).head()

Out [15]
```

| Title | Rank | Studio | Gross | Year |
|-------------------------|------|-------------|----------|------|
| The Blair Witch Project | 588 | Artisan | \$248.60 | 1999 |
| 101 Dalmatians | 708 | Buena Vista | \$215.90 | 1961 |
| The Jungle Book | 755 | Buena Vista | \$205.80 | 1967 |
| Who Framed Roger Rabbit | 410 | Buena Vista | \$329.80 | 1988 |
| Dead Poets Society | 636 | Buena Vista | \$235.90 | 1989 |

We can also sort the index, which is helpful if we want to see the movies in alphabetical order:

```
In [16] movies.sort_index().head()
```

```
Out [16]
```

| Title | Rank | Studio | Gross | Year |
|------------------|------|-----------------|----------|------|
| 10,000 B.C. | 536 | Warner Brothers | \$269.80 | 2008 |
| 101 Dalmatians | 708 | Buena Vista | \$215.90 | 1996 |
| 101 Dalmatians | 425 | Buena Vista | \$320.70 | 1996 |
| 2 Fast 2 Furious | 632 | Universal | \$236.40 | 2003 |
| 2012 | 93 | Sony | \$769.70 | 2009 |

The operations we've performed so far return *new* DataFrame objects. Pandas has not altered the original movies DataFrame from the CSV file. The nondestructive nature of these operations is beneficial; it actively encourages experimentation. We can always confirm that a result is correct before making it permanent.

1.3.3 Counting values in a Series

Let's try a more sophisticated analysis. What if we wanted to find out which movie studio had the greatest number of highest-grossing films? To solve this problem, we'll need to count the number of times each studio appears in the Studio column.

We can extract a single column of data from a DataFrame as a Series. Notice that pandas preserves the DataFrame's index, the movie titles, in the Series:

```
In [17] movies["Studio"]
```

```
Out [17] Title
```

| | |
|--|-----------------|
| Avengers: Endgame | Buena Vista |
| Avatar | Fox |
| Titanic | Paramount |
| Star Wars: The Force Awakens | Buena Vista |
| Avengers: Infinity War | Buena Vista |
| | ... |
| Yogi Bear | Warner Brothers |
| Garfield: The Movie | Fox |
| Cats & Dogs | Warner Brothers |
| The Hunt for Red October | Paramount |
| Valkyrie | MGM |
| Name: Studio, Length: 782, dtype: object | |

If a Series has a large number of rows, pandas truncates the data set to show only the first five and the last five rows.

Now that we've isolated the Studio column, we can count each unique value's number of occurrences. Let's limit our results to the top 10 studios:

```
In [18] movies["Studio"].value_counts().head(10)
```

| | |
|-----------------|-----|
| Warner Brothers | 132 |
| Buena Vista | 125 |
| Fox | 117 |

```
Universal          109
Sony              86
Paramount         76
Dreamworks        27
Lionsgate          21
New Line           16
MGM               11
Name: Studio, dtype: int64
```

The return value above is yet another `Series` object! This time around, pandas uses the studios from the `Studio` column as the index labels and their counts as the `Series` values.

1.3.4 Filtering a column by one or more criteria

You'll often want to extract a subset of rows based on one or more criteria. Excel offers the Filter tool for this exact purpose.

What if we wanted to find only the films released by Universal Studios? We can accomplish this task with one line of code in pandas:

```
In [19] movies[movies["Studio"] == "Universal"]
```

```
Out [19]
```

| Title | Rank | Studio | Gross | Year |
|--------------------------------|------|-----------|------------|------|
| Jurassic World | 6 | Universal | \$1,671.70 | 2015 |
| Furious 7 | 8 | Universal | \$1,516.00 | 2015 |
| Jurassic World: Fallen Kingdom | 13 | Universal | \$1,309.50 | 2018 |
| The Fate of the Furious | 17 | Universal | \$1,236.00 | 2017 |
| Minions | 19 | Universal | \$1,159.40 | 2015 |
| ... | ... | ... | ... | ... |
| The Break-Up | 763 | Universal | \$205.00 | 2006 |
| Everest | 766 | Universal | \$203.40 | 2015 |
| Patch Adams | 772 | Universal | \$202.30 | 1998 |
| Kindergarten Cop | 775 | Universal | \$202.00 | 1990 |
| Straight Outta Compton | 776 | Universal | \$201.60 | 2015 |

109 rows × 4 columns

We can assign the filtering condition to a variable to provide context for readers:

```
In [20] released_by_universal = (movies["Studio"] == "Universal")
       movies[released_by_universal].head()
```

```
Out [20]
```

| Title | Rank | Studio | Gross | Year |
|--------------------------------|------|-----------|------------|------|
| Jurassic World | 6 | Universal | \$1,671.70 | 2015 |
| Furious 7 | 8 | Universal | \$1,516.00 | 2015 |
| Jurassic World: Fallen Kingdom | 13 | Universal | \$1,309.50 | 2018 |
| The Fate of the Furious | 17 | Universal | \$1,236.00 | 2017 |
| Minions | 19 | Universal | \$1,159.40 | 2015 |

We can also filter DataFrame rows by multiple criteria. The next example targets all movies released by Universal Studios *and* released in 2015:

```
In [21] released_by_universal = movies["Studio"] == "Universal"
       released_in_2015 = movies["Year"] == 2015
       movies[released_by_universal & released_in_2015]

Out [21]
```

| Title | Rank | Studio | Gross | Year |
|------------------------|------|-----------|------------|------|
| Jurassic World | 6 | Universal | \$1,671.70 | 2015 |
| Furious 7 | 8 | Universal | \$1,516.00 | 2015 |
| Minions | 19 | Universal | \$1,159.40 | 2015 |
| Fifty Shades of Grey | 165 | Universal | \$571.00 | 2015 |
| Pitch Perfect 2 | 504 | Universal | \$287.50 | 2015 |
| Ted 2 | 702 | Universal | \$216.70 | 2015 |
| Everest | 766 | Universal | \$203.40 | 2015 |
| Straight Outta Compton | 776 | Universal | \$201.60 | 2015 |

The previous example includes rows that satisfied both conditions. We can also filter for films that fit either condition: released by Universal *or* released in 2015. The resulting DataFrame is longer because more films have a chance of satisfying one of the two conditions instead of both:

```
In [22] released_by_universal = movies["Studio"] == "Universal"
       released_in_2015 = movies["Year"] == 2015
       movies[released_by_universal | released_in_2015]
```

```
Out [22]
```

| Title | Rank | Studio | Gross | Year |
|--------------------------------|------|-------------|------------|------|
| Star Wars: The Force Awakens | 4 | Buena Vista | \$2,068.20 | 2015 |
| Jurassic World | 6 | Universal | \$1,671.70 | 2015 |
| Furious 7 | 8 | Universal | \$1,516.00 | 2015 |
| Avengers: Age of Ultron | 9 | Buena Vista | \$1,405.40 | 2015 |
| Jurassic World: Fallen Kingdom | 13 | Universal | \$1,309.50 | 2018 |
| ... | ... | ... | ... | ... |
| The Break-Up | 763 | Universal | \$205.00 | 2006 |
| Everest | 766 | Universal | \$203.40 | 2015 |
| Patch Adams | 772 | Universal | \$202.30 | 1998 |
| Kindergarten Cop | 775 | Universal | \$202.00 | 1990 |
| Straight Outta Compton | 776 | Universal | \$201.60 | 2015 |

140 rows × 4 columns

Pandas provides additional ways to filter a DataFrame. We can target column values less than or greater than a specific value, for example. Here, we target movies released before 1975:

```
In [23] before_1975 = movies["Year"] < 1975
      movies[before_1975]
```

Out [23]

| Title | Rank | Studio | Gross | Year |
|--------------------|------|-----------------|----------|------|
| The Exorcist | 252 | Warner Brothers | \$441.30 | 1973 |
| Gone with the Wind | 288 | MGM | \$402.40 | 1939 |
| Bambi | 540 | RKO | \$267.40 | 1942 |
| The Godfather | 604 | Paramount | \$245.10 | 1972 |
| 101 Dalmatians | 708 | Buena Vista | \$215.90 | 1961 |
| The Jungle Book | 755 | Buena Vista | \$205.80 | 1967 |

We can also specify a range between which all values must fall. The next example pulls out movies released between 1983 and 1986:

```
In [24] mid_80s = movies["Year"].between(1983, 1986)
      movies[mid_80s]
```

Out [24]

| Title | Rank | Studio | Gross | Year |
|--------------------------------------|------|-----------|----------|------|
| Return of the Jedi | 222 | Fox | \$475.10 | 1983 |
| Back to the Future | 311 | Universal | \$381.10 | 1985 |
| Top Gun | 357 | Paramount | \$356.80 | 1986 |
| Indiana Jones and the Temple of Doom | 403 | Paramount | \$333.10 | 1984 |
| Crocodile Dundee | 413 | Paramount | \$328.20 | 1986 |
| Beverly Hills Cop | 432 | Paramount | \$316.40 | 1984 |
| Rocky IV | 467 | MGM | \$300.50 | 1985 |
| Rambo: First Blood Part II | 469 | TriStar | \$300.40 | 1985 |
| Ghostbusters | 485 | Columbia | \$295.20 | 1984 |
| Out of Africa | 662 | Universal | \$227.50 | 1985 |

We can also use the DataFrame index to filter rows. The next example lowercases the movie titles in the index and finds all movies with the word "dark" in their title:

```
In [25] has_dark_in_title = movies.index.str.lower().str.contains("dark")
      movies[has_dark_in_title]
```

Out [25]

| Title | Rank | Studio | Gross | Year |
|--------------------------------|------|-----------------|------------|------|
| Transformers: Dark of the Moon | 23 | Paramount | \$1,123.80 | 2011 |
| The Dark Knight Rises | 27 | Warner Brothers | \$1,084.90 | 2012 |
| The Dark Knight | 39 | Warner Brothers | \$1,004.90 | 2008 |
| Thor: The Dark World | 132 | Buena Vista | \$644.60 | 2013 |
| Star Trek Into Darkness | 232 | Paramount | \$467.40 | 2013 |
| Fifty Shades Darker | 309 | Universal | \$381.50 | 2017 |
| Dark Shadows | 600 | Warner Brothers | \$245.50 | 2012 |
| Dark Phoenix | 603 | Fox | \$245.10 | 2019 |

Notice that pandas finds all movies containing the word "dark" irrespective of where the text appears in the title.

1.3.5 Grouping data

Our next challenge is the most complex one yet. We might be curious which studio had the highest total grosses across all films. Let's aggregate the values in the Gross column by studio.

Our first dilemma is that the Gross column's values are stored as text rather than as numbers. Pandas imported the column's values as text to preserve the dollar signs and comma symbols in the original CSV. We can convert the column's values to decimal numbers, but only if we remove both of those characters. The next example replaces all occurrences of "\$" and "," with empty text. This operation is similar to Find and Replace in Excel:

```
In [26] movies["Gross"].str.replace(
    "$", "", regex = False
).str.replace(",", "", regex = False)

Out [26] Title
        Avengers: Endgame      2796.30
        Avatar                  2789.70
        Titanic                 2187.50
        Star Wars: The Force Awakens  2068.20
        Avengers: Infinity War   2048.40
                                ...
        Yogi Bear                201.60
        Garfield: The Movie      200.80
        Cats & Dogs              200.70
        The Hunt for Red October  200.50
        Valkyrie                 200.30
Name: Gross, Length: 782, dtype: object
```

With the symbols gone, we can convert the Gross column's values from text to floating-point numbers:

```
In [27] (
    movies["Gross"]
    .str.replace("$", "", regex = False)
    .str.replace(",", "", regex = False)
    .astype(float)
)

Out [27] Title
        Avengers: Endgame      2796.3
        Avatar                  2789.7
        Titanic                 2187.5
        Star Wars: The Force Awakens  2068.2
        Avengers: Infinity War   2048.4
                                ...
        Yogi Bear                201.6
        Garfield: The Movie      200.8
        Cats & Dogs              200.7
        The Hunt for Red October  200.5
        Valkyrie                 200.3
Name: Gross, Length: 782, dtype: float64
```

Once again, these operations are temporary and do not modify the original Gross Series. In all the previous examples, pandas created a copy of the original data structure, performed the operation, and returned a new object. The next example explicitly overwrites the Gross column in movies with a new column of decimal-point numbers. Now the transformation is permanent:

```
In [28] movies["Gross"] = (
    movies["Gross"]
    .str.replace("$", "", regex = False)
    .str.replace(", ", "", regex = False)
    .astype(float)
)
```

Our data type conversion opens the door to more calculations and manipulations. The next example calculates the average box-office gross of the movies:

```
In [29] movies["Gross"].mean()

Out [29] 439.0308184143222
```

Let's return to our original problem: calculating the aggregate box-office grosses per film studio. First, we'll need to identify the studios and bucket the movies (or rows) that belong to each one. This process is called *grouping*. In the next example, we group the DataFrame's rows based on values in the Studio column:

```
In [30] studios = movies.groupby("Studio")
```

We can ask pandas to count the number of films per studio:

```
In [31] studios["Gross"].count().head()

Out [31] Studio
        Artisan          1
        Buena Vista      125
        CL                1
        China Film Corporation 1
        Columbia          5
Name: Gross, dtype: int64
```

The previous results are sorted alphabetically by studio name. We can instead sort the Series by count of films, from most to least:

```
In [32] studios["Gross"].count().sort_values(ascending = False).head()

Out [32] Studio
        Warner Brothers    132
        Buena Vista        125
        Fox                 117
        Universal          109
        Sony                86
Name: Gross, dtype: int64
```

Next, let's add the values of the Gross column per studio. Pandas will identify the subset of movies that belong to each studio, pull out their row's respective Gross values, and sum them together:

```
In [33] studios["Gross"].sum().head()
```



```
Out [33] Studio
      Artisan          248.6
      Buena Vista     73585.0
      CL              228.1
      China Film Corporation 699.8
      Columbia        1276.6
      Name: Gross, dtype: float64
```

Again, pandas sorts the results by studio name. We want to identify the studios with the highest grosses, so let's sort the Series values in descending order. Here are the five studios with the greatest grosses:

```
In [34] studios["Gross"].sum().sort_values(ascending = False).head()
```



```
Out [34] Studio
      Buena Vista     73585.0
      Warner Brothers 58643.8
      Fox             50420.8
      Universal       44302.3
      Sony            32822.5
      Name: Gross, dtype: float64
```

With a few lines of code, we can derive some fun insights from this complex data set. The Warner Brothers studio, for example, has more movies in the list than Buena Vista, but Buena Vista has a higher cumulative gross for all films. This fact indicates that the average gross of a Buena Vista film is greater than that of a Warner Brothers film.

We have barely scratched the surface of what pandas is capable of doing. I hope that these examples have shed light on the diverse ways we can manipulate and transform data with this powerful library. We'll discuss all the code used in this chapter in much greater detail throughout the book. Next, we'll dive into a core building block of pandas: the Series object.

Summary

- Pandas is a data analysis library built on top of the Python programming language.
- Pandas excels at performing complex operations on large data sets with a terse syntax.
- Competitors to pandas include the graphical spreadsheet application Excel, the statistical programming language R, and the SAS software suite.
- Programming requires a different skill set than working with Excel or Sheets.
- Pandas can import a variety of file formats. A popular format is CSV, which separates rows with line breaks and row values with commas.

- The `DataFrame` is the primary data structure in pandas. It is effectively a table of data with multiple columns.
- The `Series` is a one-dimensional labeled array. Think of it as a single column of data.
- We can access a row in a `Series` or `DataFrame` by its row number or index label.
- We can sort a `DataFrame` by values across one or more columns.
- We can use logical conditions to extract subsets of data from a `DataFrame`.
- We bucket `DataFrame` rows based on a column's values. We can also perform aggregate operations such as sums on the resulting groups.



The Series object

This chapter covers

- Instantiating `Series` objects from lists, dictionaries, tuples, and more
- Setting a custom index on a `Series`
- Accessing attributes and invoking methods on a `Series`
- Performing mathematical operations on one or more `Series`
- Passing the `Series` to Python's built-in functions

One of pandas' core data structures, the `Series` is a one-dimensional labeled array for homogeneous data. An *array* is an ordered collection of values comparable to a Python list. The term *homogeneous* means that the values are of the same data type (all integers or all Booleans, for example).

Pandas assigns each `Series` value a *label*—an identifier we can use to locate the value. The library also assigns each `Series` value an *order*—a position in line. The order starts counting from 0; the first `Series` value occupies position 0, the second

value occupies position 1, and so on. The `Series` is a one-dimensional data structure because we need one reference point to access a value: either a label or a position.

A `Series` combines and expands the best features of Python’s native data structures. Like a list, it holds its values in a sequenced order. Like a dictionary, it assigns a key/label to each value. We gain the benefits of both of those objects plus more than 180 methods for data manipulation.

In this chapter, we’ll familiarize ourselves with the mechanics of a `Series` object, learn how to calculate the sum and average of `Series` values, apply mathematical operations to each `Series` value, and more. As a building block of pandas, the `Series` is a perfect starting point for our exploration of the library.

2.1 Overview of a Series

Let’s create some `Series` objects, shall we? We’ll begin by importing the pandas and NumPy packages with the `import` keyword; we’ll use the latter library in section 2.1.4. The popular community aliases for pandas and numpy are `pd` and `np`. We can assign an alias to an import with the `as` keyword:

```
In [1]: import pandas as pd
         import numpy as np
```

The `pd` namespace holds the top-level exports of the pandas package, a bundle of more than 100 classes, functions, exceptions, constants, and more. For more information on these concepts, see appendix B.

Think of `pd` as being the lobby to the library—an entrance room where we can access pandas’ available features. The library’s exports are available as attributes on `pd`. We can access an attribute with dot syntax:

```
pd.attribute
```

Jupyter Notebook provides a convenient autocomplete feature for use in searching for attributes. Enter the library’s name, add a dot, and press the Tab key to reveal a modal of the package’s exports. As you type additional characters, the Notebook filters the results to those that match your search term.

Figure 2.1 shows the autocomplete feature in action. After entering the capital letter `S`, we can press Tab to reveal all `pd` exports starting with that character. Note that the search is case-sensitive. If the autocomplete feature is not working, add the following code to a cell in your Notebook, execute it, and try searching again:

```
%config Completer.use_jedi = False
```

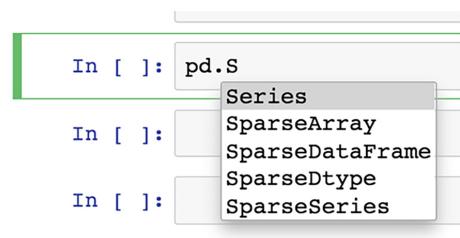


Figure 2.1 Using Jupyter Notebook’s autocomplete features to show pandas exports that start with S

We can use our keyboard’s up- and down-arrow keys to navigate the modal’s search results. Luckily, the `Series` class is our first search result. Press the Enter key to autocomplete its name.

2.1.1 Classes and instances

A *class* is a blueprint for a Python object. The `pd.Series` class is a template, and the next step is to create a concrete instance of it. We instantiate an object from a class with a pair of opening and closing parentheses. Let’s create a `Series` object from the `Series` class:

```
In [2] pd.Series()
Out [2] Series([], dtype: float64)
```

A warning might appear in a red box alongside the output:

```
DeprecationWarning: The default dtype for empty Series will be 'object'
instead of 'float64' in a future version. Specify a dtype explicitly to
silence this warning.
```

Because we did not provide any values to store, pandas could not infer the data type that the `Series` should hold. No need to worry; the warning is expected behavior.

We’ve successfully created our first `Series` object! Unfortunately, it stores no data. Let’s populate our `Series` with some values.

2.1.2 Populating the Series with values

A *constructor* is a method that builds an object from a class. When we wrote `pd.Series()` in section 2.1.1, we used the `Series` constructor to create a new `Series` object.

When we create an object, we’ll often want to define its starting state. We can think of an object’s starting state as being its initial configuration—its “settings.” We can often set state by passing arguments to the constructor that we use to create the object. An *argument* is an input we pass to a method.

Let’s practice creating some `Series` from manual data. The goal is to get comfortable with the look and feel of the data structure. In the future, we’ll use an imported data set to populate our `Series`’ values.

The first argument to the `Series` constructor is an iterable object whose values will populate the `Series`. We can pass various inputs, including lists, dictionaries, tuples, and NumPy `ndarrays`.

Let’s create a `Series` object with data from a Python list. The next example declares a list of four strings, assigns the list to an `ice_cream_flavors` variable, and then passes the list to the `Series` constructor:

```
In [3] ice_cream_flavors = [
        "Chocolate",
        "Vanilla",
        "Strawberry",
        "Rum Raisin",
    ]
```

```
pd.Series(ice_cream_flavors)

Out [3] 0      Chocolate
        1      Vanilla
        2    Strawberry
        3   Rum Raisin
       dtype: object
```

Excellent—we've created a new `Series` with the four values from our `ice_cream_flavors` list. Notice that pandas preserves the order of the strings from the input list. We'll come back to the numbers on the left of the `Series` in a moment.

A *parameter* is a name given to an expected input to a function or method. Behind the scenes, Python matches every argument we pass to a constructor with a parameter. We can view a constructor's parameters directly in Jupyter Notebook. Enter `pd.Series()` in a new cell, place the mouse cursor between the parentheses, and press Shift+Tab. Figure 2.2 shows the documentation modal that appears.

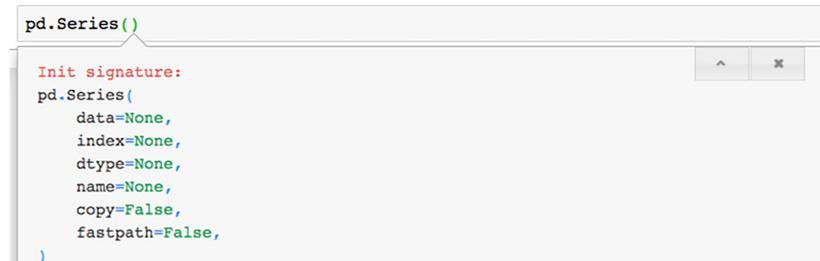


Figure 2.2 A documentation modal with the parameters and default arguments for a `Series` constructor

Press Shift+Tab repeatedly to reveal more information. Eventually, Jupyter will fix the documentation panel to the bottom of the screen.

The `Series` constructor defines six parameters: `data`, `index`, `dtype`, `name`, `copy`, and `fastpath`. We can use these parameters to set the object's initial state. We can think of the parameters as being configuration options for the `Series`.

The documentation displays each parameter alongside its default argument. A *default argument* is a fallback value that Python uses if we do not provide an argument for the parameter. If we do not pass a value for the `name` parameter, for example, Python will use `None`. A parameter with a default argument is inherently optional. It will always have some argument, either explicitly from its invocation or implicitly from its definition. We were able to instantiate a `Series` without arguments earlier because all six of its constructor's parameters are optional.

The `Series` constructor's first parameter, `data`, expects the object whose values will populate the `Series`. If we pass arguments to the constructor without parameter names, Python will assume that we are passing them sequentially. In the preceding

code example, we passed the `ice_cream_flavors` list as the first argument to the constructor; thus, Python matched it with `data`, the first constructor parameter. Python also fell back to default arguments of `None` for the `index`, `dtype`, and `name` parameters and `False` for the `copy` and `fastpath` parameters.

We can connect parameters and arguments explicitly with keyword arguments (see appendix B). Enter the parameter, followed by an equal sign and its argument. In the following example, the first line uses positional arguments, and the second one uses keyword arguments, but the result is the same:

```
In [4] # The two lines below are equivalent
      pd.Series(ice_cream_flavors)
      pd.Series(data = ice_cream_flavors)

Out [4] 0      Chocolate
        1      Vanilla
        2    Strawberry
        3   Rum Raisin
       dtype: object
```

Keyword arguments are advantageous because they provide context for what each constructor argument represents. The second line in the example better communicates that `ice_cream_flavors` represents the data for the `Series`.

2.1.3 Customizing the Series index

Let's take a closer look at our `Series`:

```
0      Chocolate
1      Vanilla
2    Strawberry
3   Rum Raisin
       dtype: object
```

Earlier, we mentioned that pandas assigns a position in line to each `Series` value. The collection of incrementing integers on the left side of the output is called the `index`. Each number signifies a value's order within the `Series`. The index starts counting from 0. The string "Chocolate" occupies index 0, the string "Vanilla" occupies index 1, and so on. In graphical spreadsheet applications, the first row of data starts counting at 1—an important difference between pandas and Excel.

The term `index` describes both the collection of identifiers and an individual identifier. Both of these two expressions are valid: "The index of the `Series` consists of integers" and "The value 'Strawberry' is found at index 2 in the `Series`."

The last index position will always be 1 less than the total number of values. The current `Series` has four ice cream flavors, so the index counts up to 3.

In addition to an index position, we can assign each `Series` value an index label. Index labels can be of any immutable data type: strings, tuples, datetimes, and more. This flexibility makes a `Series` powerful: we can reference a value by its order or by a key/label. In a sense, each value has two identifiers.

The Series constructor's second parameter, `index`, sets the index labels of the Series. If we do not pass an argument to the parameter, pandas defaults to a numeric index starting from 0. With this type of index, the label and the position identifiers are one and the same.

Let's construct a Series with a custom index. We can pass objects of different data types to the `data` and `index` parameters, but they must have the same length so that pandas can associate their values. The next example passes a list of strings for the `data` parameter and a tuple of strings to the `index` parameter. Both the list and the tuple have a length of 4:

```
In [5] ice_cream_flavors = [
    "Chocolate",
    "Vanilla",
    "Strawberry",
    "Rum Raisin",
]

days_of_week = ("Monday", "Wednesday", "Friday", "Saturday")

# The two lines below are equivalent
pd.Series(ice_cream_flavors, days_of_week)
pd.Series(data = ice_cream_flavors, index = days_of_week)

Out [5] Monday      Chocolate
       Wednesday   Vanilla
       Friday      Strawberry
       Saturday    Rum Raisin
      dtype: object
```

Pandas uses shared index positions to associate the values from the `ice_cream_flavors` list and the `days_of_week` tuple. The library sees "Rum Raisin" and "Saturday" at index position 3 in their respective objects, for example; thus, it ties them together in the Series.

Even though the index consists of string labels, pandas still assigns each Series value an index position. In other words, we can access the value "Vanilla" either by the index label "Wednesday" or by index position 1. We'll explore how to access Series elements by row and label in chapter 4.

The index permits duplicates, a detail that distinguishes a Series from a Python dictionary. In the next example, the string "Wednesday" appears twice in the Series' index labels:

```
In [6] ice_cream_flavors = [
    "Chocolate",
    "Vanilla",
    "Strawberry",
    "Rum Raisin",
]

days_of_week = ("Monday", "Wednesday", "Friday", "Wednesday")
```

```
# The two lines below are equivalent
pd.Series(ice_cream_flavors, days_of_week)
pd.Series(data = ice_cream_flavors, index = days_of_week)

Out [6] Monday      Chocolate
      Wednesday   Vanilla
      Friday      Strawberry
      Wednesday   Rum Raisin
      dtype: object
```

Although pandas permits duplicates, it is ideal to avoid them whenever possible, because a unique index allows the library to locate index labels more quickly.

One additional advantage of keyword arguments is that they permit us to pass parameters in any order. By comparison, sequential/positional arguments require us to pass arguments in the order in which the constructor expects them. The next example swaps the order of the `index` and `data` keyword parameters. Pandas creates the same `Series`:

```
In [7] pd.Series(index = days_of_week, data = ice_cream_flavors)

Out [7] Monday      Chocolate
      Wednesday   Vanilla
      Friday      Strawberry
      Wednesday   Rum Raisin
      dtype: object
```

There's one piece of the output that we haven't discussed yet: the `dtype` statement at the bottom reflects the data type of the values in the `Series`. For most data types, pandas will display a predictable type (such as `bool`, `float`, or `int`). For strings and more-complex objects (such as nested data structures), pandas will show `dtype: object`.¹

The next examples create `Series` objects from lists of Boolean, integer, and floating-point values. Observe the similarities and differences in the `Series`:

```
In [8] bunch_of_bools = [True, False, False]
      pd.Series(bunch_of_bools)

Out [8] 0      True
      1      False
      2      False
      dtype: bool

In [9] stock_prices = [985.32, 950.44]
      time_of_day = ["Open", "Close"]
      pd.Series(data = stock_prices, index = time_of_day)

Out [9] Open      985.32
      Close     950.44
      dtype: float64
```

¹ See <http://mng.bz/7j6v> for a discussion of why pandas lists “object” as the `dtype` for strings.

```
In [10] lucky_numbers = [4, 8, 15, 16, 23, 42]
       pd.Series(lucky_numbers)

Out [10] 0      4
        1      8
        2     15
        3     16
        4     23
        5    42
   dtype: int64
```

The `float64` and `int64` data types indicate that each floating-point/integer value in the Series occupies 64 bits (8 bytes) of your computer's RAM. Bits and bytes are storage units for memory. We don't need to dive extensively into these computer science concepts right now to work effectively with pandas.

Pandas does its best to infer an appropriate data type for the Series from the data parameter's values. We can force coercion to a different type via the constructor's `dtype` parameter. The next example passes an integer list to the constructor but asks for a floating-point Series:

```
In [11] lucky_numbers = [4, 8, 15, 16, 23, 42]
       pd.Series(lucky_numbers, dtype = "float")

Out [11] 0      4.0
        1      8.0
        2     15.0
        3     16.0
        4     23.0
        5    42.0
   dtype: float64
```

The previous example used both positional arguments and keyword arguments. We passed the `lucky_numbers` list sequentially to the `data` parameter. We also passed the `dtype` parameter explicitly with keyword arguments. The Series constructor expects the `dtype` parameter to be third in line, so we cannot pass it directly after `lucky_numbers`; we have to use keyword arguments.

2.1.4 Creating a Series with missing values

So far, so good. Our Series so far have been simple and complete. It's easy to have perfect data when we're crafting our own data sets. In the real world, data is a lot messier. Perhaps the most frequent problem that analysts encounter is missing values.

When pandas sees a missing value during a file import, the library substitutes NumPy's `nan` object. The acronym `nan` is short for *not a number* and is a catch-all term for an undefined value. In other words, `nan` is a placeholder object that represents nullness or absence.

Let's sneak a missing value into a Series. We assigned the NumPy library to the alias `np` when we imported it earlier. The `nan` attribute is available as a top-level export of the library. The next example nestles a `np.nan` inside a list of temperatures that we

pass to the `Series` constructor. Notice the `NaN` at index position 2 in the output. Get used to this trio of letters; we're going to be seeing them a lot throughout the book:

```
In [12] temperatures = [94, 88, np.nan, 91]
pd.Series(data = temperatures)

Out [12] 0      94.0
         1      88.0
         2      NaN
         3      91.0
dtype: float64
```

Notice that the `Series` `dtype` is `float64`. Pandas automatically converts numeric values from integers to floating-points when it spots a `nan` value; this internal technical requirement allows the library to store numeric values and missing values in the same homogeneous `Series`.

2.2 *Creating a Series from Python objects*

The `Series` constructor's `data` parameter accepts various inputs, including native Python data structures and objects from other libraries. In this section, we'll explore how the `Series` constructor deals with dictionaries, tuples, sets, and NumPy arrays. The `Series` object that `pandas` returns operates the same way irrespective of its data source.

A *dictionary* is a collection of key-value pairs (see appendix B). When passed a dictionary, the constructor sets each key as a corresponding index label in the `Series`:

```
In [13] calorie_info = {
            "Cereal": 125,
            "Chocolate Bar": 406,
            "Ice Cream Sundae": 342,
        }

        diet = pd.Series(calorie_info)
        diet

Out [13] Cereal           125
         Chocolate Bar    406
         Ice Cream Sundae  342
dtype: int64
```

A *tuple* is an immutable list. We cannot add, remove, or replace elements in a tuple after creating it (see appendix B). When passed a tuple, the constructor populates the `Series` in an expected manner:

```
In [14] pd.Series(data = ("Red", "Green", "Blue"))

Out [14] 0      Red
         1      Green
         2      Blue
dtype: object
```

To create a `Series` that stores tuples, wrap the tuples in a list. Tuples work well for row values that consist of multiple parts or components, such as an address:

```
In [15] rgb_colors = [(120, 41, 26), (196, 165, 45)]
       pd.Series(data = rgb_colors)

Out [15] 0      (120, 41, 26)
         1      (196, 165, 45)
        dtype: object
```

A *set* is an unordered collection of unique values. We can declare it with a pair of curly braces, exactly like a dictionary. Python uses the presence of key-value pairs to distinguish between the two data structures (see appendix B).

If we pass a set to the `Series` constructor, pandas raises a `TypeError` exception. A set has neither the concept of order (such as a list) nor the concept of association (such as a dictionary). Thus, the library cannot assume an order in which to store the set's values:²

```
In [16] my_set = {"Ricky", "Bobby"}
       pd.Series(my_set)

-----
TypeError                                     Traceback (most recent call last)
<ipython-input-16-bf85415a7772> in <module>
      1 my_set = {"Ricky", "Bobby" }
----> 2 pd.Series(my_set)

TypeError: 'set' type is unordered
```

If your program involves a set, transform it to an ordered data structure before passing it to the `Series` constructor. The next example converts `my_set` to a list by using Python's built-in `list` function:

```
In [17] pd.Series(list(my_set))

Out [17] 0      Ricky
         1      Bobby
        dtype: object
```

Because a set is unordered, we cannot guarantee the order of list elements (or the `Series` elements).

The `Series` constructor's `data` parameter also accepts a NumPy `ndarray` object. Many data science libraries use NumPy arrays, which are common storage formats for moving data around. The next example feeds the `Series` constructor an `ndarray` generated by NumPy's `randint` function (see appendix C):

² See “Constructing a Series with a set returns a set and not a Series,” <https://github.com/pandas-dev/pandas/issues/1913>.

```
In [18] random_data = np.random.randint(1, 101, 10)
        random_data

Out [18] array([27, 16, 13, 83, 3, 38, 34, 19, 27, 66])

In [19] pd.Series(random_data)

Out [19] 0    27
         1    16
         2    13
         3    83
         4     3
         5    38
         6    34
         7    19
         8    27
         9    66
        dtype: int64
```

As with all other inputs, pandas preserves the order of the ndarray's values in the Series.

2.3 Series attributes

An *attribute* is a piece of data belonging to an object. Attributes reveal information about the object's internal state. An attribute's value may be another object. See appendix B for an in-depth overview.

A Series is composed of several smaller objects. Think of these objects as being puzzle pieces that join to make a greater whole. Consider the calorie_info Series from section 2.2:

```
Cereal          125
Chocolate Bar   406
Ice Cream Sundae 342
dtype: int64
```

This Series uses the NumPy library's ndarray object to store the calorie counts and the pandas library's Index object to store the food names in the index. We can access these nested objects through Series attributes. The values attribute, for example, exposes the ndarray object that stores the values:

```
In [20] diet.values

Out [20] array([125, 406, 342])
```

If we're ever uncertain what type an object is or what library it comes from, we can pass the object to Python's built-in type function. The function will return the class from which the object was instantiated:

```
In [21] type(diet.values)

Out [21] numpy.ndarray
```

Let's pause here to reflect for a second. Pandas delegates the responsibility of storing Series values to an object from a different library. That's why NumPy is a dependency of pandas. The ndarray object optimizes for speed and efficiency by relying on the lower-level C programming language for many of its calculations. In many ways, the Series is a wrapper—an additional layer of functionality around a core NumPy library object.

Pandas has its own objects, of course. The index attribute, for example, returns the Index object that stores the Series labels:

```
In [22] diet.index  
Out [22] Index(['Cereal', 'Chocolate Bar', 'Ice Cream Sundae'],  
              dtype='object')
```

Index objects such as Index are built into pandas:

```
In [23] type(diet.index)  
Out [23] pandas.core.indexes.base.Index
```

Some attributes reveal helpful details about the object. dtype, for example, returns the data type of the Series' values:

```
In [24] diet.dtype  
Out [24] dtype('int64')
```

The size attribute returns the number of values in the Series:

```
In [25] diet.size  
Out [25] 3
```

The complementary shape attribute returns a tuple with the dimensions of a pandas data structure. For the one-dimensional Series, the tuple's only value will be the Series' size. The comma after the 3 is a standard visual output for one-element tuples in Python:

```
In [26] diet.shape  
Out [26] (3,)
```

The is_unique attribute returns True if all Series values are unique:

```
In [27] diet.is_unique  
Out [27] True
```

The is_unique attribute returns False if the Series contains duplicates:

```
In [28] pd.Series(data = [3, 3]).is_unique  
Out [28] False
```

The `is_monotonic` attribute returns `True` if each `Series` value is greater than the previous one. The increments between values do not have to be equal:

```
In [29] pd.Series(data = [1, 3, 6]).is_monotonic
Out [29] True
```

The `is_monotonic` attribute returns `False` if any element is smaller than the previous one:

```
In [30] pd.Series(data = [1, 6, 3]).is_monotonic
Out [30] False
```

In summary, attributes ask an object for information on its internal state. Attributes reveal nested objects, which can have their own functionalities. In Python, everything is an object, including integers, strings, and Booleans. Thus, an attribute that returns a number is no technically different from one that returns a complex object such as an `ndarray`.

2.4 **Retrieving the first and last rows**

By now, you should feel comfortable creating `Series` objects. It's OK if the technical terminology is a bit overwhelming; we've presented a lot of information up front, and we'll review it many times throughout the book. In this section, we'll start exploring what we can do with `Series` objects.

A Python object has both attributes and methods. An *attribute* is a piece of data belonging to an object—a characteristic or detail that the data structure can reveal about itself. In section 2.3, we accessed `Series` attributes such as `size`, `shape`, `values`, and `index`.

By comparison, a *method* is a function that belongs to an object—an action or command that we ask the object to perform. Methods typically involve some analysis, calculation, or manipulation of the object's attributes. Attributes define an object's *state*, and methods define an object's *behavior*.

Let's create our largest `Series` yet. We'll use Python's built-in `range` function to generate a sequence of all numbers between a starting point and an endpoint. The `range` function's three arguments are a lower bound, the upper bound, and a step sequence (the interval between every two numbers).

The next example generates a 100-value range of numbers between 0 and 500 in increments of 5 and then pass the `range` object into the `Series` constructor:

```
In [31] values = range(0, 500, 5)
        nums = pd.Series(data = values)
        nums

Out [31] 0      0
         1      5
         2     10
         3     15
         4     20
```

```
...  
95    475  
96    480  
97    485  
98    490  
99    495  
Length: 100, dtype: int64
```

Now we have a `Series` with 100 values. Fancy! Take note of the ellipses (the three dots) that appear in the middle of the output. Pandas is telling us that it condensed the output by hiding some rows. The library conveniently truncates the `Series` to show only the first five and the last five rows. Too many rows of printed data can slow Jupyter Notebook.

We invoke a method with a pair of parentheses after its name. Let's invoke some simple `Series` methods. We'll start with the `head` method, which returns rows from the beginning or top of the data set. It accepts a single argument `n`, which sets the number of rows to extract:

```
In [32] nums.head(3)  
  
Out [32] 0      0  
         1      5  
         2     10  
        dtype: int64
```

We can pass keyword arguments in method calls, as in constructors and functions. The following code produces the same result as the preceding code:

```
In [33] nums.head(n = 3)  
  
Out [33] 0      0  
         1      5  
         2     10  
        dtype: int64
```

Like functions, methods can declare default arguments for their parameters. The `head` method's `n` parameter has a default argument of 5. If we do not pass an explicit argument for `n`, pandas returns five rows (a design decision of the pandas development team):

```
In [34] nums.head()  
  
Out [34] 0      0  
         1      5  
         2     10  
         3     15  
         4     20  
        dtype: int64
```

The complementary `tail` method returns rows from the bottom or end of a `Series`:

```
In [35] nums.tail(6)

Out [35] 94    470
         95    475
         96    480
         97    485
         98    490
         99    495
dtype: int64
```

The `tail` method's `n` parameter also has a default argument of 5:

```
In [36] nums.tail()

Out [36] 95    475
         96    480
         97    485
         98    490
         99    495
dtype: int64
```

`head` and `tail` are the two methods I use most frequently; we can use them to preview the beginning and end of a data set quickly. Next, let's dive into some more-advanced `Series` methods.

2.5 Mathematical operations

A `Series` object includes plenty of statistical and mathematical methods. Let's see a few of these methods in action. Feel free to breeze through this section and revisit it when you need to track down a specific function.

2.5.1 Statistical operations

We'll begin by creating a `Series` from a list of ascending numbers, sneaking in an `np.nan` value in the middle. Remember that if a data source has even a single missing value, pandas will coerce the integers to floating-point values:

```
In [37] numbers = pd.Series([1, 2, 3, np.nan, 4, 5])
numbers

Out [37] 0    1.0
         1    2.0
         2    3.0
         3    NaN
         4    4.0
         5    5.0
dtype: float64
```

The `count` method counts the number of non-null values:

```
In [38] numbers.count()

Out [38] 5
```

The `sum` method adds the Series' values together:

```
In [39] numbers.sum()  
Out [39] 15.0
```

Most mathematical methods ignore missing values by default. We can pass an argument of `False` to the `skipna` parameter to force the inclusion of missing values.

The next example invokes the `sum` method with the parameter. Pandas returns a `nan` because it cannot add the unknown `nan` value at index 3 to the cumulative sum:

```
In [40] numbers.sum(skipna = False)  
Out [40] nan
```

The `sum` method's `min_count` parameter sets the minimum number of valid values a Series must hold for pandas to calculate its sum. Our six-element `numbers` Series contains five present values and one `nan` value

In the next example, the Series meets the threshold of three present values, so pandas returns the sum:

```
In [41] numbers.sum(min_count = 3)  
Out [41] 15.0
```

By comparison, the next invocation demands a minimum of six values for pandas to calculate the sum. The threshold is unmet, so the `sum` method returns `nan`:

```
In [42] numbers.sum(min_count = 6)  
Out [42] nan
```

TIP If you're ever curious about a method's parameters, press Shift+Tab between a method's parentheses to bring up the documentation in Jupyter Notebook.

The `product` method multiplies all Series values together:

```
In [43] numbers.product()  
Out [43] 120.0
```

The method also accepts `skipna` and `min_count` parameters. Here, we ask pandas to include `nan` values in the calculation:

```
In [44] numbers.product(skipna = False)  
Out [44] nan
```

The next example asks for the product of all Series values if it has at least three present ones:

```
In [45] numbers.product(min_count = 3)  
Out [45] 120.0
```

The `cumsum` (cumulative sum) method returns a new `Series` with a rolling sum of values. Each index position holds the sum of values up to and including the value at that index. A cumulative sum helps determine which values contribute most to the total:

```
In [46] numbers
```

```
Out [46] 0    1.0
        1    2.0
        2    3.0
        3    NaN
        4    4.0
        5    5.0
dtype: float64
```

```
In [47] numbers.cumsum()
```

```
Out [47] 0    1.0
        1    3.0
        2    6.0
        3    NaN
        4    10.0
        5    15.0
dtype: float64
```

Let's walk through some of the calculations in the result:

- The cumulative sum at index 0 is 1.0, the first value in the `numbers` `Series`. There is nothing to add yet.
- The cumulative sum at index 1 is 3.0, the sum of 1.0 at index 0 and 2.0 at index position 1.
- The cumulative sum at index 2 is 6.0, the sum of 1.0, 2.0, and 3.0.
- The `numbers` `Series` has a `nan` at index 3. Pandas cannot add a missing value to the cumulative sum, so it places a `nan` at the same index in the returned `Series`.
- The cumulative sum at index 4 is 10.0. Pandas adds the previous cumulative sum with the current index's value ($1.0 + 2.0 + 3.0 + 4.0$).

If we pass the `skipna` an argument of `False`, the `Series` will list the cumulative sum up to the index with the first missing value and then `NaN` for the remaining values:

```
In [48] numbers.cumsum(skipna = False)
```

```
Out [48] 0    1.0
        1    3.0
        2    6.0
        3    NaN
        4    NaN
        5    NaN
dtype: float64
```

The `pct_change` (percent change) method returns the percentage difference from one Series value to the next. At each index, pandas adds the last index's value and the current index's value and then divides the sum by the last index's value. Pandas can calculate a percentage difference only if both indexes have valid values.

The `pct_change` method defaults to a *forward-fill* strategy for missing values. With this strategy, pandas replaces a `nan` with the last valid value it encountered. Let's invoke the method and then walk through the calculations:

```
In [49]: numbers
```

```
Out[49]: 0    1.0
         1    2.0
         2    3.0
         3    NaN
         4    4.0
         5    5.0
dtype: float64
```

```
In [50]: numbers.pct_change()
```

```
Out[50]: 0      NaN
         1    1.000000
         2    0.500000
         3    0.000000
         4    0.333333
         5    0.250000
dtype: float64
```

Here's how pandas operates:

- At index 0, pandas cannot compare the value 1.0 in the `numbers` Series with any previous value. Thus, index 0 in the returned Series has a `NaN` value.
- At index 1, pandas compares index 1's value of 2.0 with index 0's value of 1.0. The percentage change between 2.0 and 1.0 is 100 (double), which translates to 1.000000 at index 1 in the returned Series.
- At index 2, pandas repeats the same operation.
- At index 3, the `numbers` Series has a `NaN` missing value. Pandas substitutes the last encountered value (3.0 from index 2) in its place. The percentage change between the substituted 3.0 at index 3 and the 3.0 at index 2 is 0.
- At index 4, pandas compares index 4's value of 4.0 with the previous row's value. It again substitutes the `nan` with the last valid value it saw, 3.0. The percentage change between 4 and 3 is 0.333333 (a 33 percent increase).

Figure 2.3 shows a visual representation of a forward-fill percentage-change calculation. The Series on the left is the starting point. The Series in the middle shows the intermediate calculations that pandas performs. The Series on the right is the final result.

| | |
|---|-----|
| 0 | 1.0 |
| 1 | 2.0 |
| 2 | 3.0 |
| 3 | NaN |
| 4 | 4.0 |
| 5 | 5.0 |

| | |
|---|---------------------|
| 0 | NaN |
| 1 | $(2.0 - 1.0) / 1.0$ |
| 2 | $(3.0 - 2.0) / 2.0$ |
| 3 | $(3.0 - 3.0) / 3.0$ |
| 4 | $(4.0 - 3.0) / 3.0$ |
| 5 | $(5.0 - 4.0) / 4.0$ |

| | |
|---|----------|
| 0 | NaN |
| 1 | 1.000000 |
| 2 | 0.500000 |
| 3 | 0.000000 |
| 4 | 0.333333 |
| 5 | 0.250000 |

Figure 2.3 A walkthrough of how the `pct_change` method calculates values with a forward-fill solution

The `fill_method` parameter customizes the protocol by which `pct_change` substitutes `NaN` values. This parameter is available across many methods, so it's worth taking the time to familiarize yourself with it. As mentioned earlier, with the default forward-fill strategy, pandas replaces a `nan` value with the *last* valid observation. We can pass the `fill_method` parameter an explicit argument of `"pad"` or `"ffill"` to achieve the same result:

```
In [51] # The three lines below are equivalent
       numbers.pct_change()
       numbers.pct_change(fill_method = "pad")
       numbers.pct_change(fill_method = "ffill")

Out [51] 0      NaN
         1    1.000000
         2    0.500000
         3    0.000000
         4    0.333333
         5    0.250000
dtype: float64
```

An alternative strategy for dealing with missing values is a *backfill* solution. With this option, pandas replaces a `nan` value with the next valid observation. Let's pass the `fill_method` parameter a value of `"bfill"` to see the results and then walk through them step by step:

```
In [52] # The two lines below are equivalent
       numbers.pct_change(fill_method = "bfill")
       numbers.pct_change(fill_method = "backfill")

Out [52] 0      NaN
         1    1.000000
         2    0.500000
         3    0.333333
         4    0.000000
         5    0.250000
dtype: float64
```

Notice that the values at index positions 3 and 4 differ between the forward-fill and backfill solutions. Here's how pandas arrives at the previous calculations:

- At index 0, pandas cannot compare the value 1.0 in the numbers Series with any previous value. Thus, index 0 in the returned Series has a NaN value.
- At index 3, pandas runs into a NaN in the numbers Series. Pandas substitutes the next valid value (4.0 at index 4) in its place. The percentage change between 4.0 at index 3 and 3.0 at index 2 in numbers is 0.33333.
- At index 4, pandas compares 4.0 with index 3's value. It again replaces the NaN at index 3 with 4.0, the next valid value available in the numbers Series. The percentage change between 4 and 4 is 0.0.

Figure 2.4 shows a visual representation of a backfill percentage-change calculation. The Series on the left is the starting point. The Series in the middle shows the intermediate calculations that pandas performs. The Series on the right is the final result.

| | |
|----------|-----|
| 0 | 1.0 |
| 1 | 2.0 |
| 2 | 3.0 |
| 3 | NaN |
| 4 | 4.0 |
| 5 | 5.0 |

| | |
|----------|---------------------|
| 0 | NaN |
| 1 | $(2.0 - 1.0) / 1.0$ |
| 2 | $(3.0 - 2.0) / 2.0$ |
| 3 | $(4.0 - 3.0) / 3.0$ |
| 4 | $(4.0 - 4.0) / 4.0$ |
| 5 | $(5.0 - 4.0) / 4.0$ |

| | |
|----------|----------|
| 0 | NaN |
| 1 | 1.000000 |
| 2 | 0.500000 |
| 3 | 0.333333 |
| 4 | 0.000000 |
| 5 | 0.250000 |

Figure 2.4 A walkthrough of how the `pct_change` method calculates values with a backfill solution

The `mean` method returns the average of the values in the Series. An average is the result of dividing the sum of values by the count of values:

```
In [53]: numbers.mean()
Out [53]: 3.0
```

The `median` method returns the middle number in a sorted Series of values. Half of the Series values will be below the median, and half of the values will be above the median:

```
In [54]: numbers.median()
Out [54]: 3.0
```

The `std` method returns the *standard deviation*, a measure of the variation in the data:

```
In [55]: numbers.std()
Out [55]: 1.5811388300841898
```

The `max` and `min` methods retrieve the largest and smallest value from the Series:

```
In [56]: numbers.max()
Out [56]: 5.0
```

```
In [57] numbers.min()  
Out [57] 1.0
```

Pandas sorts a string `Series` alphabetically. The “smallest” string is the one closest to the start of the alphabet, and the “largest” string is the one closest to the end of the alphabet. Here’s a simple example with a small `Series`:

```
In [58] animals = pd.Series(["koala", "aardvark", "zebra"])  
        animals  
  
Out [58] 0      koala  
         1    aardvark  
         2     zebra  
        dtype: object  
  
In [59] animals.max()  
Out [59] 'zebra'  
  
In [60] animals.min()  
Out [60] 'aardvark'
```

If you’re looking for a single method to summarize a `Series` effectively, the powerful `describe` method does the trick. It returns a `Series` of statistical evaluations, including count, mean, and standard deviation:

```
In [61] numbers.describe()  
  
Out [61] count      5.000000  
        mean      3.000000  
        std       1.581139  
        min      1.000000  
        25%      2.000000  
        50%      3.000000  
        75%      4.000000  
        max      5.000000  
        dtype: float64
```

The `sample` method selects a random assortment of values from the `Series`. It is possible for the order of values to differ between the new `Series` and the original `Series`. In the next example, notice that the lack of `NaN` values from the random selection allows pandas to return a `Series` of integers. If `NaN` was even one of the values, pandas would return a `Series` of floats instead:

```
In [62] numbers.sample(3)  
  
Out [62] 1      2  
         3      4  
         2      3  
        dtype: int64
```

The `unique` method returns a NumPy `ndarray` of unique values from the `Series`. In the next example, the string "Orwell" appears twice in the `authors` `Series` but only once in the returned `ndarray`:

```
In [63] authors = pd.Series(
        ["Hemingway", "Orwell", "Dostoevsky", "Fitzgerald", "Orwell"]
    )

    authors.unique()

Out [63] array(['Hemingway', 'Orwell', 'Dostoevsky', 'Fitzgerald'],
              dtype=object)
```

The complementary `nunique` method returns the number of unique values in the Series:

```
In [64] authors.nunique()

Out [64] 4
```

The `nunique` method's return value will be equal to the length of the array that the `unique` method returns.

2.5.2 Arithmetic operations

In section 2.5.1, we practiced invoking numerous mathematical methods on our Series objects. Pandas gives us additional ways to perform arithmetic calculations with a Series. Let's start by creating a Series of integers with one missing value:

```
In [65] s1 = pd.Series(data = [5, np.nan, 15], index = ["A", "B", "C"])
       s1

Out [65] A      5.0
         B      NaN
         C     15.0
       dtype: float64
```

We can perform arithmetic on a Series with Python's standard mathematical operators:

- + for addition
- - for subtraction
- * for multiplication
- / for division

The syntax is intuitive: treat the Series as a regular operand on one side of a mathematical operator. Place the complementary value on the other side of the operator. Note that any mathematical operation with a nan yields another nan. The next example adds 3 to each value in the `s1` Series:

```
In [66] s1 + 3

Out [66] A      8.0
         B      NaN
         C     18.0
       dtype: float64
```

Some software developers might find the result surprising. How can we add an integer to a data structure? The types are seemingly incompatible. Behind the scenes, pandas is smart enough to parse our syntax and understand that we'd like to add an integer to every value in the Series, not to the Series object itself.

If you prefer a method-based approach, the add method achieves the same result:

```
In [67] s1.add(3)

Out [67] A      8.0
          B      NaN
          C     18.0
          dtype: float64
```

The next three examples show the complementary syntax options for subtraction (-), multiplication (*), and division (/). Often, there are multiple ways to accomplish the same operation in pandas:

```
In [68] # The three lines below are equivalent
        s1 - 5
        s1.sub(5)
        s1.subtract(5)

Out [68] A      0.0
          B      NaN
          C     10.0
          dtype: float64

In [69] # The three lines below are equivalent
        s1 * 2
        s1.mul(2)
        s1.multiply(2)

Out [69] A     10.0
          B      NaN
          C    30.0
          dtype: float64

In [70] # The three lines below are equivalent
        s1 / 2
        s1.div(2)
        s1.divide(2)

Out [70] A     2.5
          B      NaN
          C     7.5
          dtype: float64
```

The floor division operator (//) performs a division and removes any digits after the decimal point in the result. The regular division of 15 by 4, for example, yields 3.75. By comparison, the floor division of 15 by 4 yields 3. We can apply the operator to a Series; the alternative is to invoke the floordiv method:

```
In [71] # The two lines below are equivalent
      s1 // 4
      s1.floordiv(4)

Out [71] A    1.0
        B    NaN
        C    3.0
       dtype: float64
```

The modulo operator (%) returns the remainder of a division. Here's an example:

```
In [72] # The two lines below are equivalent
      s1 % 3
      s1.mod(3)

Out [72] A    2.0
        B    NaN
        C    0.0
       dtype: float64
```

In the previous example,

- Pandas divides the value of 5.0 at index label A by 3 and leaves a remainder of 2.0.
- Pandas cannot divide the NaN at index label B.
- Pandas divides the value of 15.0 at index label C by 3 and leaves a remainder of 0.0.

2.5.3 Broadcasting

Recall that pandas stores its `Series` values in a NumPy `ndarray` under the hood. When we use syntax such as `s1 + 3` or `s1 - 5`, pandas delegates the mathematical calculations to NumPy.

The NumPy documentation uses the term *broadcasting* to describe the derivation of one array of values from another. Without diving too much into the technical details (you don't need to understand NumPy's complexities to work effectively with pandas), the term *broadcasting* comes from a radio broadcast tower, which transmits the same signal to all recipients listening in. Syntax like `s1 + 3` means "Apply the same operation (add 3) to each value in the `Series`." Each `Series` value gets the same message, much as every person listening to the same radio station at the same time hears the same song.

Broadcasting also describes mathematical operations between multiple `Series` objects. As a rule of thumb, pandas uses shared index labels to align values across different data structures. Let's demonstrate this concept through an example. Let's instantiate two `Series` with the same three-element index:

```
In [73] s1 = pd.Series([1, 2, 3], index = ["A", "B", "C"])
      s2 = pd.Series([4, 5, 6], index = ["A", "B", "C"])
```

When we use the `+` operator with the two `Series` as operands, pandas adds the values at the same index positions:

- At index A, pandas adds the values 1 and 4 to arrive at 5.
- At index B, pandas adds the values 2 and 5 to arrive at 7.
- At index C, pandas adds the values 3 and 6 to arrive at 9.

```
In [74] s1 + s2
Out [74] A    5
          B    7
          C    9
          dtype: int64
```

Figure 2.5 offers a visualization of how pandas aligns the two `Series`.

| | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| <table border="1"> <tr><td>A</td><td>1</td></tr> <tr><td>B</td><td>2</td></tr> <tr><td>C</td><td>3</td></tr> </table> | A | 1 | B | 2 | C | 3 | + | <table border="1"> <tr><td>A</td><td>4</td></tr> <tr><td>B</td><td>5</td></tr> <tr><td>C</td><td>6</td></tr> </table> | A | 4 | B | 5 | C | 6 | = | <table border="1"> <tr><td>A</td><td>5</td></tr> <tr><td>B</td><td>7</td></tr> <tr><td>C</td><td>9</td></tr> </table> | A | 5 | B | 7 | C | 9 |
| A | 1 | | | | | | | | | | | | | | | | | | | | | |
| B | 2 | | | | | | | | | | | | | | | | | | | | | |
| C | 3 | | | | | | | | | | | | | | | | | | | | | |
| A | 4 | | | | | | | | | | | | | | | | | | | | | |
| B | 5 | | | | | | | | | | | | | | | | | | | | | |
| C | 6 | | | | | | | | | | | | | | | | | | | | | |
| A | 5 | | | | | | | | | | | | | | | | | | | | | |
| B | 7 | | | | | | | | | | | | | | | | | | | | | |
| C | 9 | | | | | | | | | | | | | | | | | | | | | |

Figure 2.5 Pandas aligns `Series` by shared index labels when performing a mathematical operation.

Here's another example of how pandas uses shared index labels to align data. Let's create another two `Series` with the standard numeric index. We'll add a missing value to each collection:

```
In [75] s1 = pd.Series(data = [3, 6, np.nan, 12])
        s2 = pd.Series(data = [2, 6, np.nan, 12])
```

Python's equality operator (`==`) compares the equality of two objects. We can use this operator to compare values across two `Series`, as in the following example. Note that pandas considers a `nan` value to be unequal to another `nan`; it cannot assume that an absent value is equal to another absent value. The method equivalent for the equality operator is `eq`:

```
In [76] # The two lines below are equivalent
        s1 == s2
        s1.eq(2)

Out [76] 0    False
         1    True
         2    False
         3    True
         dtype: bool
```

The inequality operator (`!=`) confirms whether two values are unequal. Its method equivalent is `ne`:

```
In [77] # The two lines below are equivalent
      s1 != s2
      s1.ne(s2)

Out [77] 0      True
         1     False
         2      True
         3     False
       dtype: bool
```

Comparison operations between `Series` become trickier when the indices differ. One index may have a greater or smaller number of labels, or there may be a mismatch between the labels themselves.

The next example creates two `Series` that share only two index labels, B and C:

```
In [78] s1 = pd.Series(
            data = [5, 10, 15], index = ["A", "B", "C"]
        )

        s2 = pd.Series(
            data = [4, 8, 12, 14], index = ["B", "C", "D", "E"]
        )
```

What happens when we try to add `s1` and `s2`? Pandas adds the values at the B and C labels and returns `NaN` values for the remaining indices (A, D, and E). As a reminder, any arithmetic operation with a `NaN` value always results in a `NaN`:

```
In [79] s1 + s2

Out [79] A      NaN
         B     14.0
         C     23.0
         D      NaN
         E      NaN
       dtype: float64
```

Figure 2.6 shows how pandas aligns the `s1` and `s2` `Series` and then adds their associated index values.

| | |
|---|----|
| A | 5 |
| B | 10 |
| C | 15 |

+

| | |
|---|----|
| B | 4 |
| C | 8 |
| D | 12 |
| E | 14 |

=

| | |
|---|------|
| A | NaN |
| B | 14.0 |
| C | 23.0 |
| D | NaN |
| E | NaN |

Figure 2.6 Pandas returns `NaN` whenever the `Series` do not share an index label.

In summary, pandas aligns data by shared index labels across two `Series`, substituting `NaNs` where needed.

2.6 Passing the Series to Python's built-in functions

Python's developer community likes to rally around certain design principles to ensure consistency across codebases. One example is seamless integration between library objects and Python's built-in functions. Pandas is no exception. We can pass a Series to any of Python's built-in functions and yield a predictable result. Let's create a small Series of cities in the United States:

```
In [80] cities = pd.Series(
    data = ["San Francisco", "Los Angeles", "Las Vegas", np.nan]
)
```

The `len` function returns the number of rows in a Series. The count includes missing values (NaNs):

```
In [81] len(cities)
Out [81] 4
```

As we saw earlier, the `type` function returns the class of an object. Use this function when you're uncertain about the data structure you're working with or the library it's coming from:

```
In [82] type(cities)
Out [82] pandas.core.series.Series
```

The `dir` function returns a list of an object's attributes and methods as strings. Note that the next example displays an abbreviated version of the output:

```
In [83] dir(cities)
Out [83] ['T',
 '_AXIS_ALIASES',
 '_AXIS_IALIASES',
 '_AXIS_LEN',
 '_AXIS_NAMES',
 '_AXIS_NUMBERS',
 '_AXIS_ORDERS',
 '_AXIS_REVERSED',
 '_HANDLED_TYPES',
 '__abs__',
 '__add__',
 '__and__',
 '__annotations__',
 '__array__',
 '__array_priority__',
 #...
 ]
```

A Series' values can populate a native Python data structure. The next example creates a list from our `cities` Series by using Python's `list` function:

```
In [84] list(cities)
Out [84] ['San Francisco', 'Los Angeles', 'Las Vegas', nan]
```

We can pass the Series to Python's built-in `dict` function to create a dictionary. Pandas maps the Series' index labels and values to the dictionary's keys and values:

```
In [85]: dict(cities)

Out [85]: {0: 'San Francisco', 1: 'Los Angeles', 2: 'Las Vegas', 3: nan}
```

In Python, we use the `in` keyword to check for inclusion. In pandas, we can use the `in` keyword to check whether a given value exists in the Series' index. Here's a reminder of what `cities` looks like:

```
In [86]: cities

Out [86]: 0      San Francisco
           1      Los Angeles
           2      Las Vegas
           3        NaN
          dtype: object
```

The next two examples query for "Las Vegas" and 2 in the Series' index:

```
In [87]: "Las Vegas" in cities

Out [87]: False

In [88]: 2 in cities

Out [88]: True
```

To check for inclusion among the Series' values, we can pair the `in` keyword with the `values` attribute. Remember that `values` exposes the `ndarray` object that holds the data itself:

```
In [89]: "Las Vegas" in cities.values

Out [89]: True
```

We can use the inverse `not in` operator to check for exclusion. The operator returns `True` if pandas cannot find the value in the Series:

```
In [90]: 100 not in cities

Out [90]: True

In [91]: "Paris" not in cities.values

Out [91]: True
```

A pandas object will often integrate with Python's built-in functions and offer its own attribute/method to return the same data. Choose the syntax option that works best for you.

2.7 Coding challenge

Welcome to the book's first coding challenge! The goal of these exercises is to help you apply and review the concepts introduced throughout the chapter. You'll find the solutions immediately after the questions. Good luck!

2.7.1 Problems

Suppose that you're given these two data structures:

```
In [92] superheroes = [
    "Batman",
    "Superman",
    "Spider-Man",
    "Iron Man",
    "Captain America",
    "Wonder Woman"
]

In [93] strength_levels = (100, 120, 90, 95, 110, 120)
```

Here are your challenges:

- 1 Use the list of superheroes to populate a new `Series` object.
- 2 Use the tuple of strengths to populate a new `Series` object.
- 3 Create a `Series` with the superheroes as index labels and the strength levels as the values. Assign the `Series` to a `heroes` variable.
- 4 Extract the first two rows of the `heroes` `Series`.
- 5 Extract the last four rows of the `heroes` `Series`.
- 6 Determine the number of unique values in your `heroes` `Series`.
- 7 Calculate the average strength of the superheroes in `heroes`.
- 8 Calculate the maximum and minimum strengths in `heroes`.
- 9 Calculate what each superhero's strength level would be if it doubled.
- 10 Convert the `heroes` `Series` to a Python dictionary.

2.7.2 Solutions

Let's explore the solutions to the problems in section 2.7.1:

- 1 To create a new `Series` object, we can use the `Series` constructor at the top level of the pandas library. Pass in the source of data as the first positional argument:

```
In [94] pd.Series(superheroes)

Out [94] 0           Batman
          1           Superman
          2        Spider-Man
          3         Iron Man
          4   Captain America
          5      Wonder Woman
dtype: object
```

- 2 The solution to this problem is identical to the previous one; we only have to pass in our tuple of strengths to the `Series` constructor. This time around, let's write out the `data` keyword parameter explicitly:

```
In [95] pd.Series(data = strength_levels)

Out [95] 0    100
         1    120
         2     90
         3    95
         4   110
         5    120
dtype: int64
```

- 3 To create a `Series` with a custom index, we can pass the `index` parameter to the constructor. Here, we set the strength levels as the `Series`' values and the superhero names as the index labels:

```
In [96] heroes = pd.Series(
            data = strength_levels, index = superheroes
        )

heroes

Out [96] Batman      100
          Superman    120
          Spider-Man   90
          Iron Man     95
          Captain America 110
          Wonder Woman  120
dtype: int64
```

- 4 As a reminder, a *method* is an action or a command we can give to an object. We can use the `head` method to extract rows from the top of a pandas data structure. The method's only parameter, `n`, sets the number of rows to pull out. The `head` method returns a new `Series`:

```
In [97] heroes.head(2)

Out [97] Batman      100
          Superman    120
dtype: int64
```

- 5 The complementary `tail` method extracts rows from the end of a pandas data structure. To target the last four rows, we'll pass in an argument of 4:

```
In [98] heroes.tail(4)

Out [98] Spider-Man      90
          Iron Man       95
          Captain America 110
          Wonder Woman   120
dtype: int64
```

- 6 To identify the number of unique values in a Series, we can invoke the `nunique` method. The `heroes` Series has six total values and five unique values; the value 120 appears twice:

```
In [99] heroes.nunique()  
Out [99] 5
```

- 7 To calculate the average of a Series' values, we can invoke the `mean` method:

```
In [100] heroes.mean()  
Out [100] 105.83333333333333
```

- 8 The next challenge is to identify the largest and smallest values in the Series. The `max` and `min` methods do the trick:

```
In [101] heroes.max()  
Out [101] 120  
In [102] heroes.min()  
Out [102] 90
```

- 9 How can we double each superhero's strength level? We can multiply each Series value by 2. The following solution uses the multiplication operator, but the `mul` and `multiply` methods are also suitable options:

```
In [103] heroes * 2  
Out [103] Batman      200  
          Superman    240  
          Spider-Man   180  
          Iron Man     190  
          Captain America 220  
          Wonder Woman  240  
          dtype: int64
```

- 10 The last challenge is to convert the `heroes` Series to a Python dictionary. To solve this problem, we can pass the data structure into Python's `dict` constructor/function. Pandas sets the index labels as the dictionary keys and the Series values as the dictionary values:

```
In [104] dict(heroes)  
Out [104] {'Batman': 100,  
           'Superman': 120,  
           'Spider-Man': 90,  
           'Iron Man': 95,  
           'Captain America': 110,  
           'Wonder Woman': 120}
```

Congratulations on completing your first coding challenge!

Summary

- A Series is a one-dimensional homogeneous labeled array that holds values and an index.
- A Series' values can be of any data type. The index labels can be of any immutable data type.
- Pandas assigns both an index *position* and an index *label* to each Series value.
- We can populate a Series with data from lists, dictionaries, tuples, NumPy arrays, and more.
- The head method retrieves the first rows of a Series.
- The tail method retrieves the last rows of a Series.
- A Series supports common statistical operations such as sum, mean, median, and standard deviation.
- Pandas uses shared index labels to apply arithmetic operations across multiple Series.
- A Series plays friendly with Python's built-in functions, including dict, list, and len.

3

Series methods

This chapter covers

- Importing CSV data sets with the `read_csv` function
- Sorting `Series` values in ascending and descending order
- Retrieving the largest and smallest values in a `Series`
- Counting occurrences of unique values in a `Series`
- Invoking a function with every value in a `Series`

In chapter 2, we began exploring the `Series` object, a one-dimensional labeled array of homogeneous values. We populated our `Series` with data from different sources, including lists, dictionaries, and NumPy `ndarrays`. We observed how pandas assigned each `Series` value an index label and an index position. We learned how to apply mathematical operations to `Series`.

With the basics under our belt, we're ready to explore some real-world data sets! In this chapter, we'll introduce lots of advanced `Series` operations, including sorting, counting, and bucketing. We'll also start to see how these methods can help us derive insights from our data. Let's dive in.

3.1 Importing a data set with the `read_csv` function

A CSV is a plain-text file that separates each row of data with a line break and each row value with a comma. The first row in the file holds the column headers for the data. This chapter has three CSV files for us to play with:

- *pokemon.csv*—A list of more than 800 Pokémons, the cartoon monsters from Nintendo's popular media franchise. Each Pokémon has one or more associated *types*, such as Fire, Water, and Grass.
- *google_stock.csv*—A collection of daily stock prices in U.S. dollars for the technology company Google from its market debut in August 2004 to October 2019.
- *revolutionary_war.csv*—A record of battles during the American Revolutionary War. Each skirmish is associated with a start date and a U.S. state.

Let's begin by importing the data sets. As we proceed, we'll talk through some optimizations we can make to pave the way for easier analysis.

Our first step is spinning up a new Jupyter Notebook and importing the pandas library. Make sure to create the notebook in the same directory as the CSV files:

```
In [1] import pandas as pd
```

Pandas has more than a dozen import functions to load various file formats. The functions are available at the library's top level and begin with the prefix `read`. In our case, to import a CSV, we want the `read_csv` function. The function's first parameter, `filepath_or_buffer`, expects a string with the filename. Make sure that the string includes the `.csv` extension ("`pokemon.csv`", for example, instead of "`pokemon`"). By default, pandas looks for the file in the same directory as the Notebook:

```
In [2] # The two lines below are equivalent
      pd.read_csv(filepath_or_buffer = "pokemon.csv")
      pd.read_csv("pokemon.csv")
```

```
Out [2]
```

| | Pokemon | Type |
|-----|-------------|----------------|
| 0 | Bulbasaur | Grass / Poison |
| 1 | Ivysaur | Grass / Poison |
| 2 | Venusaur | Grass / Poison |
| 3 | Charmander | Fire |
| 4 | Charmeleon | Fire |
| ... | ... | ... |
| 804 | Stakataka | Rock / Steel |
| 805 | Blacephalon | Fire / Ghost |
| 806 | Zeraora | Electric |
| 807 | Meltan | Steel |
| 808 | Melmetal | Steel |

```
809 rows × 2 columns
```

Regardless of the number of columns in a data set, the `read_csv` function always imports the data into a `DataFrame`, a two-dimensional pandas data structure that supports multiple rows and columns. We'll introduce this object in greater detail in chapter 4. There's nothing wrong with using the `DataFrame`, but we want to practice a bit more with the `Series`, so let's store the CSV's data in the smaller data structure.

Our first issue is that the data set has two columns (`Pokemon` and `Type`), but a `Series` supports only one column of data. One simple solution is setting one of the data set's columns as the `Series` index. We can use the `index_col` parameter to set the index column. Be mindful of case sensitivity: the string must match the header in the data set. Let's pass "`Pokemon`" as the argument to `index_col`:

```
In [3] pd.read_csv("pokemon.csv", index_col = "Pokemon")
```

```
Out [3]
```

| Pokemon | Type |
|----------------|----------------|
| Bulbasaur | Grass / Poison |
| Ivysaur | Grass / Poison |
| Venusaur | Grass / Poison |
| Charmander | Fire |
| Charmeleon | Fire |
| ... | ... |
| Stakataka | Rock / Steel |
| Blacephalon | Fire / Ghost |
| Zeraora | Electric |
| Meltan | Steel |
| Melmetal | Steel |

```
809 rows × 1 columns
```

We've successfully set the `Pokemon` column as the `Series` index, but pandas still defaults to importing the data into a `DataFrame`. After all, a container capable of holding multiple columns of data can technically hold one column of data. To force pandas to use a `Series`, we need to add another parameter called `squeeze` and pass it an argument of `True`. The `squeeze` parameter coerces a one-column `DataFrame` into a `Series`:

```
In [4] pd.read_csv("pokemon.csv", index_col = "Pokemon", squeeze = True)
```

```
Out [4] Pokemon
       Bulbasaur    Grass / Poison
       Ivysaur      Grass / Poison
       Venusaur     Grass / Poison
       Charmander    Fire
       Charmeleon    Fire
       ...
       Stakataka    Rock / Steel
       Blacephalon   Fire / Ghost
       Zeraora       Electric
       Meltan         Steel
       Melmetal       Steel
Name: Type, Length: 809, dtype: object
```

We officially have a `Series`. Hooray! The index labels are the Pokémon names, and the values are the Pokémon types.

The output below the values reveals some important details:

- Pandas has assigned the `Series` a name of `Type`, the column's name from the CSV file.
- The `Series` has 809 values.
- `dtype: object` tells us that it's a `Series` of string values. `object` is pandas' internal lingo for strings and more-complex data structures.

The final step is assigning the `Series` to a variable. `pokemon` feels suitable here:

```
In [5] pokemon = pd.read_csv(
    "pokemon.csv", index_col = "Pokemon", squeeze = True
)
```

The remaining two data sets carry some additional complexity. Let's take a peek at `google_stock.csv`:

```
In [6] pd.read_csv("google_stocks.csv").head()
Out [6]
```

| | Date | Close |
|---|------------|-------|
| 0 | 2004-08-19 | 49.98 |
| 1 | 2004-08-20 | 53.95 |
| 2 | 2004-08-23 | 54.50 |
| 3 | 2004-08-24 | 52.24 |
| 4 | 2004-08-25 | 52.80 |

When importing a data set, pandas infers the most suitable data type for each column. Sometimes, the library plays it safe and avoids making assumptions about our data. `google_stocks.csv`, for example, includes a `Date` column with datetime values in YYYY-MM-DD format (such as 2010-08-04). Unless we tell pandas to treat the values as datetimes, the library defaults to importing them as strings. A string is a more generic and versatile data type; it can represent any value.

Let's explicitly tell pandas to convert the values in the `Date` column to datetimes. Although we won't cover datetimes until chapter 11, it's considered to be a best practice to store each column's data in the most accurate type. When pandas knows that it has datetimes, it enables additional methods that are not available on plain strings, such as calculating the weekday of a date.

The `read_csv` function's `parse_dates` parameter accepts a list of strings denoting the columns whose text values pandas should convert to datetimes. The next example passes a list containing "`Date`".

```
In [7] pd.read_csv("google_stocks.csv", parse_dates = ["Date"]).head()
Out [7]
```

| | Date | Close |
|---|------------|-------|
| 0 | 2004-08-19 | 49.98 |
| 1 | 2004-08-20 | 53.95 |

```
2 2004-08-23 54.50
3 2004-08-24 52.24
4 2004-08-25 52.80
```

There is no visual difference in the output, but pandas is storing a different data type for the Date column under the hood. Let's set the Date column as the Series index with the `index_col` parameter; a Series works fine with datetime indexes. Finally, let's add the `squeeze` parameter to force a Series object instead of a DataFrame:

```
In [8] pd.read_csv(
    "google_stocks.csv",
    parse_dates = ["Date"],
    index_col = "Date",
    squeeze = True
).head()

Out [8] Date
2004-08-19      49.98
2004-08-20      53.95
2004-08-23      54.50
2004-08-24      52.24
2004-08-25      52.80
Name: Close, dtype: float64
```

Looks good. We have a Series of datetime index labels and floating-point values. Let's save this Series to a `google` variable:

```
In [9] google = pd.read_csv(
    "google_stocks.csv",
    parse_dates = ["Date"],
    index_col = "Date",
    squeeze = True
)
```

We have one more data set to import: Revolutionary War battles. This time around, let's preview the last five rows on import. We'll chain the `tail` method to the DataFrame returned by the `read_csv` function:

```
In [10] pd.read_csv("revolutionary_war.csv").tail()
```

```
Out [10]
```

| | Battle | Start Date | State |
|-----|----------------------------|-------------------|--------------|
| 227 | Siege of Fort Henry | 9/11/1782 | Virginia |
| 228 | Grand Assault on Gibraltar | 9/13/1782 | NaN |
| 229 | Action of 18 October 1782 | 10/18/1782 | NaN |
| 230 | Action of 6 December 1782 | 12/6/1782 | NaN |
| 231 | Action of 22 January 1783 | 1/22/1783 | Virginia |

Take a look at the State column. Uh-oh—this data set has some missing values. As a reminder, pandas uses the `NaN` (not a number) designation to mark absent values. `NaN` is a NumPy object used to represent nothingness or the absence of a value. This data set contains missing/absent values for battles without a definitive start date or those fought outside U.S. territory.

Let's set the Start Date column as the index. We'll again use the `index_col` parameter to set the index and the `parse_dates` parameter to convert the Start Date strings to datetime values. Pandas can recognize this data set's date format (M/D/YYYY):

```
In [11] pd.read_csv(
    "revolutionary_war.csv",
    index_col = "Start Date",
    parse_dates = ["Start Date"],
).tail()

Out [11]
          Battle      State
Start Date
1782-09-11   Siege of Fort Henry  Virginia
1782-09-13  Grand Assault on Gibraltar     NaN
1782-10-18  Action of 18 October 1782     NaN
1782-12-06  Action of 6 December 1782     NaN
1783-01-22  Action of 22 January 1783  Virginia
```

By default, the `read_csv` function imports all columns from a CSV. We'll have to limit the import to two columns if we want a `Series`: one column for the index and the other for the values. The `squeeze` parameter by itself is insufficient in this scenario; pandas will ignore the parameter if there is more than one column of data.

The `read_csv` function's `usecols` parameter accepts a list of columns that pandas should import. Let's include only Start Date and State:

```
In [12] pd.read_csv(
    "revolutionary_war.csv",
    index_col = "Start Date",
    parse_dates = ["Start Date"],
    usecols = ["State", "Start Date"],
    squeeze = True
).tail()

Out [12] Start Date
1782-09-11      Virginia
1782-09-13        NaN
1782-10-18        NaN
1782-12-06        NaN
1783-01-22      Virginia
Name: State, dtype: object
```

Perfect! We have a `Series` consisting of a datetime index and string values. Let's assign this one to a `battles` variable:

```
In [13] battles = pd.read_csv(
    "revolutionary_war.csv",
    index_col = "Start Date",
    parse_dates = ["Start Date"],
    usecols = ["State", "Start Date"],
    squeeze = True
)
```

Now that we've imported our data sets into `Series` objects, let's see what we can do with them.

3.2 Sorting a Series

We can sort a `Series` by its values or its index, in ascending or descending order.

3.2.1 Sorting by values with the `sort_values` method

Suppose that we're curious about the lowest and highest stock prices that Google has had. The `sort_values` method returns a new `Series` with the values sorted in ascending order. *Ascending* means increasing in size—in other words, smallest to greatest. The index labels move with their value counterparts:

```
In [14] google.sort_values()

Out [14] Date
2004-09-03    49.82
2004-09-01    49.94
2004-08-19    49.98
2004-09-02    50.57
2004-09-07    50.60
...
2019-04-23    1264.55
2019-10-25    1265.13
2018-07-26    1268.33
2019-04-26    1272.18
2019-04-29    1287.58
Name: Close, Length: 3824, dtype: float64
```

Pandas sorts a `Series` of strings in alphabetical order. *Ascending* means from the start of the alphabet to the end of the alphabet:

```
In [15] pokemon.sort_values()

Out [15] Pokemon
Illumise          Bug
Silcoon           Bug
Pinsir            Bug
Burmy             Bug
Wurmple           Bug
...
Tirtouga          Water / Rock
Relicanth         Water / Rock
Corsola            Water / Rock
Carracosta         Water / Rock
Empoleon           Water / Steel
Name: Type, Length: 809, dtype: object
```

Pandas sorts uppercase characters before lowercase characters. Thus, a capital "Z" comes before a lowercase "a". In the next example, notice that the string "adam" appears *after* "Ben":

```
In [16] pd.Series(data = ["Adam", "adam", "Ben"]).sort_values()

Out [16] 0      Adam
         2      Ben
         1     adam
        dtype: object
```

The `ascending` parameter sets the sort order, and it has a default argument of `True`. To sort `Series` values in descending order (largest to smallest), pass the parameter an argument of `False`:

```
In [17] google.sort_values(ascending = False).head()

Out [17] Date
         2019-04-29    1287.58
         2019-04-26    1272.18
         2018-07-26    1268.33
         2019-10-25    1265.13
         2019-04-23    1264.55
        Name: Close, dtype: float64
```

A descending sort will arrange a `Series` of strings in reverse alphabetical order. *Descending* means from the end of the alphabet to the start of the alphabet:

```
In [18] pokemon.sort_values(ascending = False).head()

Out [18] Pokemon
         Empoleon    Water / Steel
         Carracosta   Water / Rock
         Corsola      Water / Rock
         Relicanth    Water / Rock
         Tirtouga     Water / Rock
        Name: Type, dtype: object
```

The `na_position` parameter configures the placement of `NaN` values in the returned `Series` and has a default argument of `"last"`. By default, pandas places missing values at the end of a sorted `Series`:

```
In [19] # The two lines below are equivalent
        battles.sort_values()
        battles.sort_values(na_position = "last")

Out [19] Start Date
         1781-09-06 Connecticut
         1779-07-05 Connecticut
         1777-04-27 Connecticut
         1777-09-03 Delaware
         1777-05-17 Florida
         ...
         1782-08-08      NaN
         1782-08-25      NaN
         1782-09-13      NaN
         1782-10-18      NaN
         1782-12-06      NaN
        Name: State, Length: 232, dtype: object
```

To display the missing values first, pass the `na_position` parameter an argument of "first". The resulting Series shows all NaNs first, followed by the sorted values:

```
In [20] battles.sort_values(na_position = "first")

Out [20] Start Date
1775-09-17      NaN
1775-12-31      NaN
1776-03-03      NaN
1776-03-25      NaN
1776-05-18      NaN
...
1781-07-06  Virginia
1781-07-01  Virginia
1781-06-26  Virginia
1781-04-25  Virginia
1783-01-22  Virginia
Name: State, Length: 232, dtype: object
```

What if we wanted to remove NaN values? The `dropna` method returns a Series with all missing values removed. Note that the method targets only NaNs in the Series' values, not the index. The next example filters our battles to those with a present location:

```
In [21] battles.dropna().sort_values()

Out [21] Start Date
1781-09-06  Connecticut
1779-07-05  Connecticut
1777-04-27  Connecticut
1777-09-03  Delaware
1777-05-17  Florida
...
1782-08-19  Virginia
1781-03-16  Virginia
1781-04-25  Virginia
1778-09-07  Virginia
1783-01-22  Virginia
Name: State, Length: 162, dtype: object
```

The previous Series is predictably shorter than `battles`. Pandas has removed 70 NaN values from `battles`.

3.2.2 ***Sorting by index with the sort_index method***

Sometimes, our area of focus may lie in the index rather than the values. Luckily, we can sort a Series by index as well with the `sort_index` method. With this option, the values move alongside their index counterparts. Like `sort_values`, `sort_index` accepts an `ascending` parameter, and its default argument is also True:

```
In [22] # The two lines below are equivalent
pokemon.sort_index()
pokemon.sort_index(ascending = True)
```

```
Out [22] Pokemon
      Abomasnow      Grass / Ice
      Abra          Psychic
      Absol          Dark
      Accelgor       Bug
      Aegislash     Steel / Ghost
      ...
      Zoroark        Dark
      Zorua          Dark
      Zubat         Poison / Flying
      Zweilous      Dark / Dragon
      Zygarde        Dragon / Ground
Name: Type, Length: 809, dtype: object
```

When sorting a collection of datetimes in ascending order, pandas sorts from the earliest date to the latest. The `battles` Series offers a great opportunity to see this sort in action:

```
In [23] battles.sort_index()

Out [23] Start Date
      1774-09-01    Massachusetts
      1774-12-14    New Hampshire
      1775-04-19    Massachusetts
      1775-04-19    Massachusetts
      1775-04-20      Virginia
      ...
      1783-01-22      Virginia
      NaT            New Jersey
      NaT            Virginia
      NaT            NaN
      NaT            NaN
Name: State, Length: 232, dtype: object
```

We see a new type of value toward the end of the sorted `Series`. Pandas uses another NumPy object, `NaT`, in place of missing date values (`NaT` stands for not a time). The `NaT` object maintains data integrity with the index's datetime type.

The `sort_index` method also includes the `na_position` parameter for altering the placement of `NaN` values. The next example displays the missing values first, followed by the sorted datetimes:

```
In [24] battles.sort_index(na_position = "first").head()

Out [24] Start Date
      NaT            New Jersey
      NaT            Virginia
      NaT            NaN
      NaT            NaN
      1774-09-01    Massachusetts
Name: State, dtype: object
```

To sort in descending order, we can pass the `ascending` parameter an argument of `False`. A descending sort displays dates from latest to earliest:

```
In [25] battles.sort_index(ascending = False).head()

Out [25] Start Date
          1783-01-22    Virginia
          1782-12-06      NaN
          1782-10-18      NaN
          1782-09-13      NaN
          1782-09-11    Virginia
Name: State, dtype: object
```

The data set's earliest battle took place on January 22, 1783, in Virginia.

3.2.3 ***Retrieving the smallest and largest values with the nsmallest and nlargest methods***

Suppose that we wanted to find the five dates on which Google's stock performed best. One option is to sort the `Series` in descending order and then limit the results to the first five rows:

```
In [26] google.sort_values(ascending = False).head()

Out [26] Date
          2019-04-29    1287.58
          2019-04-26    1272.18
          2018-07-26    1268.33
          2019-10-25    1265.13
          2019-04-23    1264.55
Name: Close, dtype: float64
```

The operation is fairly common, so pandas offers a helper method to save us a few characters. The `nlargest` method returns the largest values from a `Series`. Its first parameter, `n`, sets the number of records to return. The `n` parameter has a default argument of 5. Pandas sorts the values in descending order in the returned `Series`:

```
In [27] # The two lines below are equivalent
        google.nlargest(n = 5)
        google.nlargest()

Out [27] Date
          2019-04-29    1287.58
          2019-04-26    1272.18
          2018-07-26    1268.33
          2019-10-25    1265.13
          2019-04-23    1264.55
Name: Close, dtype: float64
```

The complementary `nsmallest` method returns the smallest values from a `Series`, sorted in ascending order. Its `n` parameter also has a default argument of 5:

```
In [28] # The two lines below are equivalent
        google.nsmallest(n = 5)
        google.nsmallest(5)
```

```
Out [28] Date
        2004-09-03    49.82
        2004-09-01    49.94
        2004-08-19    49.98
        2004-09-02    50.57
        2004-09-07    50.60
        2004-08-30    50.81
Name: Close, dtype: float64
```

Note that neither of these methods works on Series of strings.

3.3 Overwriting a Series with the `inplace` parameter

All the methods that we've invoked in this chapter return new Series objects. The original Series objects referenced by our `pokemon`, `google`, and `battles` variables have remained unaffected throughout our operations thus far. As an example, let's observe `battles` before and after a method call; the Series does not change:

```
In [29] battles.head(3)

Out [29] Start Date
        1774-09-01    Massachusetts
        1774-12-14    New Hampshire
        1775-04-19    Massachusetts
Name: State, dtype: object

In [30] battles.sort_values().head(3)

Out [30] Start Date
        1781-09-06    Connecticut
        1779-07-05    Connecticut
        1777-04-27    Connecticut
Name: State, dtype: object

In [31] battles.head(3)

Out [31] Start Date
        1774-09-01    Massachusetts
        1774-12-14    New Hampshire
        1775-04-19    Massachusetts
Name: State, dtype: object
```

What if we wanted to modify the `battles` Series? Many methods in pandas include an `inplace` parameter that, when passed an argument of `True`, appears to modify the object on which the method is invoked.

Compare the previous example with the next one. Here, we once again invoke the `sort_values` method, but this time around, we pass an argument of `True` to the `inplace` parameter. If we use `inplace`, the method returns `None`, leading to no output in Jupyter Notebook. When we output `battles`, we can see that it has changed:

```
In [32] battles.head(3)

Out [32] Start Date
        1774-09-01    Massachusetts
        1774-12-14    New Hampshire
        1775-04-19    Massachusetts
Name: State, dtype: object
```

```
In [33] battles.sort_values(inplace = True)

In [34] battles.head(3)

Out [34] Start Date
          1781-09-06    Connecticut
          1779-07-05    Connecticut
          1777-04-27    Connecticut
Name: State, dtype: object
```

The `inplace` parameter is a frequent point of confusion. Its name suggests that it modifies or mutates the existing object rather than creating a copy. Developers are tempted to use `inplace` because reducing the number of copies we create decreases memory use. But even with the `inplace` parameter, pandas creates a copy of an object whenever we invoke a method. The library *always* creates a duplicate; the `inplace` parameter reassigns our existing variable to the new object. Thus, contrary to popular belief, the `inplace` parameter does not offer any performance benefits. These two lines are technically equivalent:

```
battles.sort_values(inplace = True)
battles = battles.sort_values()
```

Why did the pandas developers choose this implementation? What advantage do we gain from always creating copies? You can find more detailed explanations online, but the short answer is that immutable data structures tend to lead to fewer bugs. Remember that an immutable object is incapable of change. We can copy an immutable object and manipulate the copy, but we can't alter the original object. A Python string is an example. An immutable object is less likely to enter a corrupted or invalid state; it is also easier to test.

The pandas development team has discussed removing the `inplace` parameter from the library in future versions. My recommendation is to avoid using it if possible. The alternative solution is to reassign a method's return value to the same variable or create a separate, more descriptive variable. We can assign the `sort_values` method return value to a variable such as `sorted_battles`, for example.

3.4 Counting values with the `value_counts` method

Here's a reminder of what the `pokemon` Series looks like:

```
In [35] pokemon.head()

Out [35] Pokemon
          Bulbasaur      Grass / Poison
          Ivysaur        Grass / Poison
          Venusaur      Grass / Poison
          Charmander       Fire
          Charmeleon       Fire
Name: Type, dtype: object
```

How can we find out the most common types of Pokémons? We need to group the values into buckets and count the number of elements in each bucket. The

value_counts method, which counts the number of occurrences of each Series value, solves the problem perfectly:

```
In [36]: pokemon.value_counts()

Out [36]:
Normal           65
Water            61
Grass             38
Psychic          35
Fire              30
..
Fire / Dragon     1
Dark / Ghost      1
Steel / Ground    1
Fire / Psychic     1
Dragon / Ice       1
Name: Type, Length: 159, dtype: int64
```

The value_counts method returns a new Series object. The index labels are the pokemon Series' values, and the values are their respective counts. Sixty-five of the Pokémons are classified as Normal, 61 are classified as Water, and so on. For those who are curious, “Normal” Pokémons are those that excel in physical attacks.

The length of the value_counts Series is equal to the number of unique values in the pokemon Series. As a reminder, the nunique method returns this piece of information:

```
In [37]: len(pokemon.value_counts())
Out [37]: 159

In [38]: pokemon.nunique()
Out [38]: 159
```

Data integrity is paramount in situations like these. The presence of an extra space or the different casing of a character will cause pandas to deem two values unequal and count them separately. We'll discuss data cleanup in chapter 6.

The value_counts method's ascending parameter has a default argument of False. Pandas sorts the values in descending order, from most occurrences to least occurrences. To sort the values in ascending order, pass the ascending parameter a value of True:

```
In [39]: pokemon.value_counts(ascending = True)

Out [39]:
Rock / Poison        1
Ghost / Dark         1
Ghost / Dragon        1
Fighting / Steel      1
Rock / Fighting        1
..
Fire                  30
Psychic               35
Grass                  38
Water                  61
Normal                 65
```

We may be more interested in the ratio of a Pokémon type relative to all the types. Set the `value_counts` method's `normalize` parameter to `True` to return the frequencies of each unique value. A value's frequency is the portion of the data set that the value makes up:

```
In [40] pokémon.value_counts(normalize = True).head()

Out [40] Normal      0.080346
         Water       0.075402
         Grass        0.046972
         Psychic     0.043263
         Fire         0.037083
```

We can multiply the values in the frequency `Series` by 100 to get the percentage each Pokémon type contributes to the whole. Do you recall the syntax from chapter 2? We can use a plain mathematical operator like a multiplication symbol with a `Series`. Pandas will apply the operation to each value:

```
In [41] pokémon.value_counts(normalize = True).head() * 100

Out [41] Normal      8.034611
         Water       7.540173
         Grass        4.697157
         Psychic     4.326329
         Fire         3.708282
```

Normal Pokémon make up 8.034611% of the data set, Water Pokémon make up 7.540173%, and so on. Interesting!

Let's say we wanted to limit the precision of the percentages. We can round a `Series`' values with the `round` method. The method's first parameter, `decimals`, sets the number of digits to leave after the decimal point. The next example rounds the values to two digits; it wraps code from the previous example in parentheses to avoid a syntactical error. We want to make sure that pandas first multiplies each value by 100 and then invokes `round` on the resulting `Series`:

```
In [42] (pokémon.value_counts(normalize = True) * 100).round(2)

Out [42] Normal      8.03
         Water       7.54
         Grass        4.70
         Psychic     4.33
         Fire         3.71
         ...
         Rock / Fighting 0.12
         Fighting / Steel 0.12
         Ghost / Dragon 0.12
         Ghost / Dark   0.12
         Rock / Poison   0.12
Name: Type, Length: 159, dtype: float64
```

The `value_counts` method operates identically on a numeric `Series`. The next example counts the occurrences of each unique stock price in the `google` `Series`. It turns out that no stock price appears more than three times in the data set:

```
In [43] google.value_counts().head()

Out [43] 237.04      3
          288.92      3
          287.68      3
          290.41      3
          194.27      3
```

To identify trends in numeric data sets, it can be more beneficial to group values into predefined intervals rather than count distinct values. Let's begin by determining the difference between the smallest and largest values within the `google` Series. The Series' `max` and `min` methods work well here. An alternative option is passing the Series into Python's built-in `max` and `min` functions:

```
In [44] google.max()

Out [44] 1287.58

In [45] google.min()

Out [45] 49.82
```

We have a range of ~1,250 between the smallest and largest values. Let's group the stock prices into buckets of 200, starting at 0 and working up to 1,400. We can define these intervals as values in a list and pass the list to the `value_counts` method's `bins` parameter. Pandas will use every two subsequent list values as the lower and upper ends of an interval:

```
In [46] buckets = [0, 200, 400, 600, 800, 1000, 1200, 1400]
        google.value_counts(bins = buckets)

Out [46] (200.0, 400.0]      1568
          (-0.001, 200.0]      595
          (400.0, 600.0]      575
          (1000.0, 1200.0]    406
          (600.0, 800.0]      380
          (800.0, 1000.0]     207
          (1200.0, 1400.0]     93
          Name: Close, dtype: int64
```

The output tells us that Google's stock price was between \$200 and \$400 for 1,568 values in the data set.

Note that pandas sorted the previous Series in descending order by the number of values in each bucket. What if we wanted to sort the results by the intervals instead? We simply have to mix and match a few pandas methods. The intervals are the index labels in the returned Series, so we can use the `sort_index` method to sort them. This technique of invoking multiple methods in sequence is called *method chaining*:

```
In [47] google.value_counts(bins = buckets).sort_index()

Out [47] (-0.001, 200.0]      595
          (200.0, 400.0]      1568
          (400.0, 600.0]      575
          (600.0, 800.0]      380
```

```
(800.0, 1000.0]      207
(1000.0, 1200.0]    406
(1200.0, 1400.0]    93
Name: Close, dtype: int64
```

We can achieve an identical result by passing a value of `False` to the `sort` parameter of the `value_counts` method:

```
In [48] google.value_counts(bins = buckets, sort = False)

Out [48] (-0.001, 200.0]      595
          (200.0, 400.0]      1568
          (400.0, 600.0]      575
          (600.0, 800.0]      380
          (800.0, 1000.0]     207
          (1000.0, 1200.0]    406
          (1200.0, 1400.0]    93
          Name: Close, dtype: int64
```

Notice that the first interval includes the value `-0.001` instead of `0`. When pandas organizes the `Series`' values into buckets, it may extend any bin's range up to `.1%` in either direction. The symbols around intervals have significance:

- A parenthesis marks a value as *excluded* from the interval.
- A square bracket marks a value as *included* in the interval.

Consider the interval `(-0.001, 200.0]`. `-0.001` is excluded, and `200` is included. Thus, the interval captures all values greater than `-0.001` and less than or equal to `200.0`.

A *closed interval* includes both endpoints. An example is `[5, 10]` (greater than or equal to `5`, less than or equal to `10`).

An *open interval* excludes both endpoints. An example is `(5, 10)` (greater than `5`, less than `10`).

The `value_counts` method with a `bin` parameter returns *half-open* intervals. Pandas will include one of the endpoints and exclude the other.

The `value_counts` method's `bins` parameter also accepts an integer argument. Pandas will automatically calculate the difference between the maximum and minimum values in the `Series` and divide the range into the specified number of bins. The next example splits the stock prices in `google` into six bins. Note that the bins/buckets may not be perfectly equal in size (due to the possible `.1%` extension of any interval in any direction) but will be reasonably close:

```
In [49] google.value_counts(bins = 6, sort = False)

Out [49] (48.581, 256.113]      1204
          (256.113, 462.407]    1104
          (462.407, 668.7]      507
          (668.7, 874.993]      380
          (874.993, 1081.287]   292
          (1081.287, 1287.58]   337
          Name: Close, dtype: int64
```

What about our battles data set? We haven't seen it for a while:

```
In [50] battles.head()

Out [50] Start Date
        1781-09-06    Connecticut
        1779-07-05    Connecticut
        1777-04-27    Connecticut
        1777-09-03    Delaware
        1777-05-17    Florida
Name: State, dtype: object
```

We can use the `value_counts` method to see which states had the most battles in the Revolutionary War:

```
In [51] battles.value_counts().head()

Out [51] South Carolina      31
          New York            28
          New Jersey           24
          Virginia             21
          Massachusetts        11
Name: State, dtype: int64
```

Pandas will exclude `NaN` values from the `value_counts` Series by default. Pass the `dropna` parameter an argument of `False` to count null values as a distinct category:

```
In [52] battles.value_counts(dropna = False).head()

Out [52] NaN                  70
          South Carolina      31
          New York            28
          New Jersey           24
          Virginia             21
Name: State, dtype: int64
```

A Series index also supports the `value_counts` method. We have to access the `index` object via the `index` attribute before invoking the method. Let's find out which dates had the most battles during the Revolutionary War:

```
In [53] battles.index

Out [53]

DatetimeIndex(['1774-09-01', '1774-12-14', '1775-04-19', '1775-04-19',
               '1775-04-20', '1775-05-10', '1775-05-27', '1775-06-11',
               '1775-06-17', '1775-08-08',
               ...
               '1782-08-08', '1782-08-15', '1782-08-19', '1782-08-26',
               '1782-08-25', '1782-09-11', '1782-09-13', '1782-10-18',
               '1782-12-06', '1783-01-22'],
              dtype='datetime64[ns]', name='Start Date', length=232,
              freq=None)
```

```
In [54] battles.index.value_counts()

Out [54]
1775-04-19    2
1781-05-22    2
1781-04-15    2
1782-01-11    2
1780-05-25    2
...
1778-05-20    1
1776-06-28    1
1777-09-19    1
1778-08-29    1
1777-05-17    1
Name: Start Date, Length: 217, dtype: int64
```

It looks as though no date saw more than two battles.

3.5 Invoking a function on every Series value with the apply method

A function is a *first-class object* in Python, which means that the language treats it like any other data type. A function may feel like a more abstract entity, but it's as valid a data structure as any other.

Here's the simplest way to think about first-class objects. Anything that you can do with a number, you can do with a function. You can do all the following things, for example:

- Store a function in a list.
- Assign a function as a value for a dictionary key.
- Pass a function into another function as an argument.
- Return a function from another function.

It's important to distinguish between a function and a function invocation. A *function* is a sequence of instructions that produces an output; it is a "recipe" that has not been cooked yet. By comparison, a *function invocation* is the actual execution of the instructions; it is the cooking of the recipe.

The next example declares a `funcs` list that stores three Python built-in functions. The `len`, `max`, and `min` functions are not invoked within the list. The list stores references to the functions themselves:

```
In [55] funcs = [len, max, min]
```

The next example iterates over the `funcs` list with a `for` loop. Over three iterations, the `current_func` iterator variable represents the uninvoked `len`, `max`, and `min` functions. During each iteration, the loop invokes the dynamic `current_func` function, passes in the `google` Series, and prints the return value:

```
In [56] for current_func in funcs:
        print(current_func(google))

Out [56]
3824
1287.58
49.82
```

The output includes the sequential return values of the three functions: the length of the Series, the maximum value in the Series, and the minimum value in the Series.

The key takeaway here is that we can treat a function like any other object in Python. So how does this fact apply to pandas? Suppose that we want to round each floating-point value in our `google` Series up or down to the closest integer. Python has a convenient `round` function for this purpose. The function rounds a value above 0.5 up and any value below 0.5 down:

```
In [57]: round(99.2)
Out [57]: 99
In [58]: round(99.49)
Out [58]: 99
In [59]: round(99.5)
Out [59]: 100
```

Wouldn't it be great if we could apply this `round` function to every value in our Series? We're in luck. The Series has a method called `apply` that invokes a function once for each Series value and returns a new Series consisting of the return values of the function invocations. The `apply` method expects the function it will invoke as its first parameter, `func`. The next example passes Python's built-in `round` function:

```
In [60]: # The two lines below are equivalent
          google.apply(func = round)
          google.apply(round)

Out [60]: Date
          2004-08-19      50
          2004-08-20      54
          2004-08-23      54
          2004-08-24      52
          2004-08-25      53
          ...
          2019-10-21     1246
          2019-10-22     1243
          2019-10-23     1259
          2019-10-24     1261
          2019-10-25     1265
Name: Close, Length: 3824, dtype: int64
```

We've rounded every Series value!

Again, please take a moment to notice that we're passing the `apply` method the uninvoked `round` function. We're passing in the recipe. Somewhere in the internals of pandas, the `apply` method knows to invoke our function on every Series value. Pandas abstracts away the complexity of the operation.

The `apply` method also accepts custom functions. Define the function to accept a single parameter and have it return the value that you'd like pandas to store in the aggregated `Series`.

Let's say we wanted to find out how many of our Pokémons have one type (such as Fire) and how many have two or more types. We need to apply the same logic, the categorization of a Pokémon, to each `Series` value. A function is an ideal container for encapsulating that logic. Let's define a utility function called `single_or_multi` that accepts a single Pokémon type and determines whether it has one or several types. If a Pokémon has multiple types, the string separates them with a slash ("Fire / Ghost"). We can use Python's `in` operator to check for the inclusion of a forward slash in the argument string. The `if` statement executes a block only if its condition evaluates to `True`. In our case, if a `/` is present, the function will return the string "Multi"; otherwise, it'll return "Single":

```
In [61] def single_or_multi(pokemon_type):
    if "/" in pokemon_type:
        return "Multi"
    else:
        return "Single"
```

Now we can pass the `single_or_multi` function to the `apply` method. Here's a quick refresher on what `pokemon` looks like:

```
In [62] pokemon.head(4)

Out [62] Pokemon
         Bulbasaur      Grass / Poison
         Ivysaur       Grass / Poison
         Venusaur      Grass / Poison
         Charmander        Fire
Name: Type, dtype: object
```

The next example calls the `apply` method with the `single_or_multi` function as its argument. Pandas invokes the `single_or_multi` function for every `Series` value:

```
In [63] pokemon.apply(single_or_multi)

Out [63] Pokemon
         Bulbasaur      Multi
         Ivysaur       Multi
         Venusaur      Multi
         Charmander     Single
         Charmeleon     Single
                     ...
         Stakataka      Multi
         Blacephalon    Multi
         Zeraora        Single
         Meltan         Single
         Melmetal        Single
Name: Type, Length: 809, dtype: object
```

Our first specimen, Bulbasaur, is classified as a Grass / Poison Pokémon, so the `single_or_multi` function returns "Multi". By comparison, our fourth specimen, Charmander, is classified as a Fire Pokémon, so the function returns "Single". The same logic repeats for the remaining pokémon values.

We have a new `Series` object! Let's find out how many Pokémon fall into each classification by invoking `value_counts`:

```
In [64] pokemon.apply(single_or_multi).value_counts()  
Out [64] Multi      405  
        Single     404  
        Name: Type, dtype: int64
```

It turns out that there's a fairly even split of single-power and multipower Pokémon. I hope that this knowledge will prove to be useful at some point in your life.

3.6 Coding challenge

Let's tackle a challenge that combines several ideas introduced in this chapter and chapter 2.

3.6.1 Problems

Suppose that a historian reaches out to us and asks us to determine which day of the week saw the most battles during the Revolutionary War. The final output should be a `Series` with the days (Sunday, Monday, and so on) as index labels and a count of battles on each day as the values. Starting from scratch, import the `revolutionary_war.csv` data set, and perform the necessary operations to arrive at the following data:

```
Saturday      39  
Friday        39  
Wednesday    32  
Thursday      31  
Sunday        31  
Tuesday       29  
Monday        27
```

You'll need one additional piece of Python knowledge to solve this problem. If you have a single `datetime` object, you can invoke the `strftime` method on it with an argument of "%A" to return the day of a week a date falls on (such as "Sunday"). See the following example and appendix B for a more-extensive overview of a `datetime` object:

```
In [65] import datetime as dt  
        today = dt.datetime(2020, 12, 26)  
        today.strftime("%A")  
  
Out [65] 'Saturday'
```

HINT Declaring a custom function to calculate a date's day of the week may prove to be helpful.

Good luck!

3.6.2 Solutions

Let's reimport the `revolutionary_war.csv` data set and remind ourselves of its original shape:

```
In [66] pd.read_csv("revolutionary_war.csv").head()
```

```
Out [66]
```

| | Battle | Start Date | State |
|---|-----------------------------------|------------|---------------|
| 0 | Powder Alarm | 9/1/1774 | Massachusetts |
| 1 | Storming of Fort William and Mary | 12/14/1774 | New Hampshire |
| 2 | Battles of Lexington and Concord | 4/19/1775 | Massachusetts |
| 3 | Siege of Boston | 4/19/1775 | Massachusetts |
| 4 | Gunpowder Incident | 4/20/1775 | Virginia |

We do not need the Battle and State columns for this analysis. You're welcome to use either column as the index or stick with the default numeric one.

The critical step is coercing the string values in the Start Date column to datetimes. If we're working with dates, we can invoke date-related methods such as `strftime`. We do not have the same power with plain strings. Let's select the Start Date column with the `usecols` parameter and convert its values to datetimes with the `parse_dates` parameter. Finally, remember to pass `True` to the `squeeze` parameter to create a Series instead of a DataFrame:

```
In [67] days_of_war = pd.read_csv(
        "revolutionary_war.csv",
        usecols = ["Start Date"],
        parse_dates = ["Start Date"],
        squeeze = True,
    )

days_of_war.head()

Out [67] 0    1774-09-01
         1    1774-12-14
         2    1775-04-19
         3    1775-04-19
         4    1775-04-20
Name: Start Date, dtype: datetime64[ns]
```

Our next challenge is extracting the day of the week for each date. One solution (using only the tools we know now) is to pass each Series value to a function that will return that date's day of the week. Let's declare that function now:

```
In [68] def day_of_week(date):
        return date.strftime("%A")
```

How can we invoke the `day_of_week` function once for each Series value? We can pass the `day_of_week` function as the argument to the `apply` method. We expect to get the days of the week, except that...

```
In [69] days_of_war.apply(day_of_week)

-----
ValueError                                     Traceback (most recent call last)
<ipython-input-411-c133befd2940> in <module>
-----> 1 days_of_war.apply(day_of_week)

ValueError: NaTType does not support strftime
```

Uh-oh—our Start Date column has missing values. Unlike a datetime object, a NaT object does not have a strftime method, so pandas runs into trouble when passing it into the day_of_week function. The simple solution is to drop all missing datetime values from the Series before we call the apply method. We can do so with the dropna method:

```
In [70] days_of_war.dropna().apply(day_of_week)
```

```
Out [70] 0      Thursday
        1      Wednesday
        2      Wednesday
        3      Wednesday
        4      Thursday
        ...
       227     Wednesday
       228     Friday
       229     Friday
       230     Friday
       231     Wednesday
Name: Start Date, Length: 228, dtype: object
```

Now we're getting somewhere! We need a way to count the number of occurrences for each weekday. The value_counts method does the trick:

```
In [71] days_of_war.dropna().apply(day_of_week).value_counts()

Out [71] Saturday    39
        Friday      39
        Wednesday   32
        Thursday    31
        Sunday      31
        Tuesday     29
        Monday      27
Name: Start Date, dtype: int64
```

Perfect! The result is a tie between Friday and Saturday. Congratulations on completing the coding challenge!

Summary

- The read_csv function imports a CSV's contents into a pandas data structure.
- The read_csv function's parameters can customize the imported columns, the index, the data types, and more.

- The `sort_values` method sorts a `Series`' values in ascending or descending order.
- The `sort_index` method sorts a `Series`' index in ascending or descending order.
- We can use the `inplace` parameter to reassign the copy returned from a method to the original variable holding an object. There are no performance benefits to using `inplace`.
- The `value_counts` method counts the occurrences of each unique value in a `Series`.
- The `apply` method invokes a function on each `Series` value and returns the results in a new `Series`.

The DataFrame object

This chapter covers

- Instantiating DataFrame objects from dictionaries and NumPy ndarrays
- Importing DataFrames from CSV files with the `read_csv` function
- Sorting DataFrame columns
- Accessing rows and columns in a DataFrame
- Setting and resetting a DataFrame index
- Renaming columns and index labels in a DataFrame

The pandas DataFrame is a two-dimensional table of data with rows and columns. As with a Series, pandas assigns an index label and an index position to each DataFrame row. Pandas also assigns a label and a position to each column. The DataFrame is two-dimensional because it requires two points of reference—a row and a column—to isolate a value from the data set. Figure 4.1 displays a visual example of a pandas DataFrame.

| | Column A | Column B |
|-------|----------|----------|
| Row A | | |
| Row B | | |
| Row C | | |
| Row D | | |
| Row E | | |

Figure 4.1 A visual representation of a pandas DataFrame with five rows and two columns

The DataFrame is the workhorse of the pandas library and the data structure you'll be working with most on a daily basis, so we'll be spending the remainder of this book exploring its vast features.

4.1 Overview of a DataFrame

As always, let's spin up a new Jupyter Notebook and import pandas. We also need the NumPy library, which we'll use in section 4.1.2 to generate random data. NumPy is usually assigned the alias np:

```
In [1] import pandas as pd
      import numpy as np
```

The DataFrame class constructor is available at the top level of pandas. The syntax for instantiating a DataFrame object is identical to the one for instantiating a Series. We access the DataFrame class and instantiate with a pair of parentheses: pd.DataFrame().

4.1.1 Creating a DataFrame from a dictionary

The constructor's first parameter, data, expects the data that will populate the DataFrame. One suitable input is a Python dictionary in which the keys are column names and the values are column values. The next example passes a dictionary of string keys and list values. Pandas returns a DataFrame with three columns. Each list element becomes a value in its respective column:

```
In [2] city_data = {
        "City": ["New York City", "Paris", "Barcelona", "Rome"],
        "Country": ["United States", "France", "Spain", "Italy"],
        "Population": [8600000, 2141000, 5515000, 2873000]
    }

cities = pd.DataFrame(city_data)
cities
```

```
Out [2]
```

| | City | Country | Population |
|---|---------------|---------------|------------|
| 0 | New York City | United States | 8600000 |
| 1 | Paris | France | 2141000 |
| 2 | Barcelona | Spain | 5515000 |
| 3 | Rome | Italy | 2873000 |

We officially have a DataFrame! Notice that the data structure is rendered differently from a Series.

A DataFrame holds an index of row labels. We did not provide the constructor a custom index, so pandas generated a numeric one starting at 0. The logic operates the same way it does on a Series.

A DataFrame can hold multiple columns of data. It's helpful to think of the column headers as a second index. City, Country, and Population are three index labels on the column axis; pandas assigns them the index positions 0, 1, and 2, respectively.

What if we wanted to swap the column headers with the index labels? Two options are available here. We can invoke the transpose method on the DataFrame or access its T attribute:

```
In [3] # The two lines below are equivalent
      cities.transpose()
      cities.T
```

```
Out [3]
```

| | 0 | 1 | 2 | 3 |
|------------|---------------|---------|-----------|---------|
| City | New York City | Paris | Barcelona | Rome |
| Country | United States | France | Spain | Italy |
| Population | 8600000 | 2141000 | 5515000 | 2873000 |

The previous example serves as a reminder that pandas can store index labels of different data types. In the previous output, the columns use the same value for index labels and index positions. The rows have different labels (City, Country, Population) and positions (0, 1, and 2).

4.1.2 Creating a DataFrame from a NumPy ndarray

Let's try one more example. The DataFrame constructor's data parameter also accepts a NumPy ndarray. We can generate an ndarray of any size with the randint function in NumPy's random module. The next example creates a 3×5 ndarray of integers between 1 and 101 (exclusive):

```
In [4] random_data = np.random.randint(1, 101, [3, 5])
      random_data

Out [4] array([[25, 22, 80, 43, 42],
               [40, 89, 7, 21, 25],
               [89, 71, 32, 28, 39]])
```

If you'd like more information on random data generation in NumPy, see appendix C.

Next, let's pass our ndarray into the DataFrame constructor. The ndarray has neither row labels nor column labels. Thus, pandas uses a numeric index for both the row axis and column axis:

```
In [5] pd.DataFrame(data = random_data)

Out [5]
      0   1   2   3   4
0  25  22  80  43  42
1  40  89   7  21  25
2  89  71  32  28  39
```

We can manually set the row labels with the `DataFrame` constructor's `index` parameter, which accepts any iterable object, including a list, tuple, or `ndarray`. Note that the iterable's length must be equal to the data set's number of rows. We're passing a 3×5 `ndarray`, so we must provide three row labels:

```
In [6] row_labels = ["Morning", "Afternoon", "Evening"]
       temperatures = pd.DataFrame(
           data = random_data, index = row_labels
       )
       temperatures

Out [6]
      0   1   2   3   4
Morning  25  22  80  43  42
Afternoon 40  89   7  21  25
Evening  89  71  32  28  39
```

We can set the column names with the constructor's `columns` parameter. The `ndarray` includes five columns, so we must pass an iterable with five items. The next example passes the column names in a tuple:

```
In [7] row_labels = ["Morning", "Afternoon", "Evening"]
       column_labels = (
           "Monday",
           "Tuesday",
           "Wednesday",
           "Thursday",
           "Friday",
       )
       pd.DataFrame(
           data = random_data,
           index = row_labels,
           columns = column_labels,
       )
```

```
Out [7]
      Monday Tuesday Wednesday Thursday Friday
Morning     25        22       80      43     42
Afternoon    40        89        7      21     25
Evening     89        71       32      28     39
```

Pandas permits duplicates in the row and column indices. In the next example, "Morning" appears twice in the rows' index labels, and "Tuesday" appears twice in the columns' index labels:

```
In [8] row_labels = ["Morning", "Afternoon", "Morning"]
      column_labels = [
          "Monday",
          "Tuesday",
          "Wednesday",
          "Tuesday",
          "Friday"
      ]
      pd.DataFrame(
          data = random_data,
          index = row_labels,
          columns = column_labels,
      )
Out [8]
```

| | Monday | Tuesday | Wednesday | Tuesday | Friday |
|-----------|---------------|----------------|------------------|----------------|---------------|
| Morning | 25 | 22 | 80 | 43 | 42 |
| Afternoon | 40 | 89 | 7 | 21 | 25 |
| Evening | 89 | 71 | 32 | 28 | 39 |

As we mentioned in earlier chapters, it's ideal to have unique indices when possible. If there are no duplicates, it is easier for pandas to extract a specific row or column.

4.2 Similarities between Series and DataFrames

Many Series attributes and methods are also available on DataFrames. Their implementations can vary; pandas must account for multiple columns and two separate axes now.

4.2.1 Importing a DataFrame with the `read_csv` function

The nba.csv data set is a list of professional basketball players in the National Basketball Association (NBA) during the 2019–20 season. Each row includes a player's name, team, position, birthday, and salary. A good mix of data types is scattered throughout, making this data set excellent for exploring the basics of DataFrames.

Let's use the `read_csv` function at the top level of pandas to import the file (we introduced this function in chapter 3). The function accepts a filename as its first argument and returns a DataFrame by default. Before you execute the following code, please make sure that the data set is in the same directory as your Jupyter Notebook:

```
In [9] pd.read_csv("nba.csv")
```

```
Out [9]
```

| | Name | Team | Position | Birthday | Salary |
|-----|----------------|--------------------|-----------------|-----------------|---------------|
| 0 | Shake Milton | Philadelphia 76ers | SG | 9/26/96 | 1445697 |
| 1 | Christian Wood | Detroit Pistons | PF | 9/27/95 | 1645357 |
| 2 | PJ Washington | Charlotte Hornets | PF | 8/23/98 | 3831840 |
| 3 | Derrick Rose | Detroit Pistons | PG | 10/4/88 | 7317074 |
| 4 | Marial Shayok | Philadelphia 76ers | G | 7/26/95 | 79568 |
| ... | ... | ... | ... | ... | ... |
| 445 | Austin Rivers | Houston Rockets | PG | 8/1/92 | 2174310 |
| 446 | Harry Giles | Sacramento Kings | PF | 4/22/98 | 2578800 |

```

447      Robin Lopez      Milwaukee Bucks      C   4/1/88    4767000
448     Collin Sexton    Cleveland Cavaliers    PG  1/4/99    4764960
449      Ricky Rubio      Phoenix Suns       PG 10/21/90  16200000
450 rows × 5 columns

```

At the bottom of the output, pandas informs us that the data has 450 rows and 5 columns.

Before we assign the `DataFrame` to a variable, let's make one optimization. Pandas imports the `Birthday` column values as strings rather than as datetimes, limiting the number of operations we can perform on them. We can use the `parse_dates` parameter to coerce the values into datetimes:

```
In [10] pd.read_csv("nba.csv", parse_dates = ["Birthday"])

Out [10]
```

| | Name | Team | Position | Birthday | Salary |
|-----|----------------|---------------------|----------|------------|----------|
| 0 | Shake Milton | Philadelphia 76ers | SG | 1996-09-26 | 1445697 |
| 1 | Christian Wood | Detroit Pistons | PF | 1995-09-27 | 1645357 |
| 2 | PJ Washington | Charlotte Hornets | PF | 1998-08-23 | 3831840 |
| 3 | Derrick Rose | Detroit Pistons | PG | 1988-10-04 | 7317074 |
| 4 | Marial Shayok | Philadelphia 76ers | G | 1995-07-26 | 79568 |
| ... | ... | ... | ... | ... | ... |
| 445 | Austin Rivers | Houston Rockets | PG | 1992-08-01 | 2174310 |
| 446 | Harry Giles | Sacramento Kings | PF | 1998-04-22 | 2578800 |
| 447 | Robin Lopez | Milwaukee Bucks | C | 1988-04-01 | 4767000 |
| 448 | Collin Sexton | Cleveland Cavaliers | PG | 1999-01-04 | 4764960 |
| 449 | Ricky Rubio | Phoenix Suns | PG | 1990-10-21 | 16200000 |

```
450 rows × 5 columns
```

Much better! Now we have a column of datetimes. Pandas displays the datetime values in conventional YYYY-MM-DD format. I'm happy with the import, so we can assign the `DataFrame` to a variable like `nba`:

```
In [11] nba = pd.read_csv("nba.csv", parse_dates = ["Birthday"])
```

It's helpful to think of a `DataFrame` as being a collection of `Series` objects with a common index. In this example, the five columns in `nba` (Name, Team, Position, Birthday, and Salary) share the same row index. Let's get to work exploring the `DataFrame`.

4.2.2 Shared and exclusive attributes of Series and DataFrames

Attributes and methods may differ between `Series` and `DataFrames`, both in name and implementation. Here's an example. A `Series` has a `dtype` attribute that reveals the data type of its values (see chapter 2). Notice that the `dtype` attribute is singular because a `Series` can store only one data type:

```
In [12] pd.Series([1, 2, 3]).dtype

Out [12] dtype('int64')
```

By comparison, a DataFrame can hold heterogeneous data. *Heterogeneous* means mixed or varied. One column can hold integers, and another can hold strings. A DataFrame has a unique `dtypes` attribute. (Notice that the name is plural.) The attribute returns a Series with the DataFrame's columns as the index labels and the columns' data types as the values:

```
In [13] nba.dtypes
```

```
Out [13] Name          object
         Team         object
         Position      object
         Birthday    datetime64[ns]
         Salary        int64
         dtype: object
```

The Name, Team, and Position columns list `object` as their data type. The `object` data type is pandas' lingo for complex objects including strings. Thus, the `nba` DataFrame has three string columns, one datetime column, and one integer column.

We can invoke the `value_counts` method on the Series to count the number of columns storing each data type:

```
In [14] nba.dtypes.value_counts()
```

```
Out [14] object      3
         datetime64[ns] 1
         int64        1
         dtype: int64
```

`dtype` versus `dtypes` is one example of the different attributes between Series and DataFrames. But the two data structures also have many attributes and methods in common.

A DataFrame consists of several smaller objects: an index that holds the row labels, an index that holds the column labels, and a data container that holds the values. The `index` attribute exposes the index of the DataFrame:

```
In [15] nba.index
```

```
Out [15] RangeIndex(start=0, stop=450, step=1)
```

Here, we have a `RangeIndex`, an index optimized for storing a sequence of numeric values. A `RangeIndex` object includes three attributes: `start` (the inclusive lower bound), `stop` (the exclusive upper bound), and `step` (the interval or step sequence between every two values). The output above tells us that `nba`'s index starts counting at 0 and proceeds to 450 in increments of 1.

Pandas uses a separate `index` object to store a DataFrame's columns. We can access it via the `columns` attribute:

```
In [16] nba.columns
```

```
Out [16] Index(['Name', 'Team', 'Position', 'Birthday', 'Salary'],
              dtype='object')
```

This object is another type of index object: `Index`. Pandas uses this option when an index consists of text values.

The `index` attribute is an example of an attribute that a `DataFrame` shares with a `Series`. The `columns` attribute is an example of an attribute that is exclusive to a `DataFrame`. A `Series` has no concept of columns.

The `ndim` attribute returns the number of dimensions in a pandas object. A `DataFrame` has two:

```
In [17] nba.ndim
Out [17] 2
```

The `shape` attribute returns the `DataFrame`'s dimensions in a tuple. The `nba` data set has 450 rows and 5 columns:

```
In [18] nba.shape
Out [18] (450, 5)
```

The `size` attribute calculates the total number of values in the data set. Missing values (such as `NaNs`) are included in the count:

```
In [19] nba.size
Out [19] 2250
```

If we want to exclude missing values, the `count` method returns a `Series` with the counts of present values per column:

```
In [20] nba.count()
Out [20] Name      450
          Team     450
          Position  450
          Birthday 450
          Salary    450
          dtype: int64
```

We can add all these `Series` values with the `sum` method to arrive at the number of non-null values in the `DataFrame`. The `nba` `DataFrame` data set holds no missing values, so the `size` attribute and the `sum` method return the same result:

```
In [21] nba.count().sum()
Out [21] 2250
```

Here's an example illustrating the differences between the `size` attribute and the `count` method. Let's create a `DataFrame` with a missing value. We can access `nan` as a top-level attribute on the NumPy package:

```
In [22] data = {
          "A": [1, np.nan],
          "B": [2, 3]
```

```

        }

df = pd.DataFrame(data)
df

Out [22]

  A  B
0  1.0  2
1  NaN  3

```

The size attribute returns 4 because the DataFrame has four cells:

```
In [23] df.size
```

```
Out [23] 4
```

By comparison, the sum method returns 3 because the DataFrame has three non-null values:

```
In [24] df.count()
```

```
Out [24] A    1
         B    2
         dtype: int64
```

```
In [25] df.count().sum()
```

```
Out [25] 3
```

The A column has one present value, and the B column has two present values.

4.2.3 Shared methods of Series and DataFrames

DataFrames and Series have methods in common too. We can use the head method to extract rows from the top of a DataFrame, for example:

```
In [26] nba.head(2)
```

```
Out [26]
```

| | Name | Team | Position | Birthday | Salary |
|---|----------------|--------------------|----------|------------|---------|
| 0 | Shake Milton | Philadelphia 76ers | SG | 1996-09-26 | 1445697 |
| 1 | Christian Wood | Detroit Pistons | PF | 1995-09-27 | 1645357 |

The tail method returns rows from the bottom of the DataFrame:

```
In [27] nba.tail(n = 3)
```

```
Out [27]
```

| | Name | Team | Position | Birthday | Salary |
|-----|---------------|---------------------|----------|------------|----------|
| 447 | Robin Lopez | Milwaukee Bucks | C | 1988-04-01 | 4767000 |
| 448 | Collin Sexton | Cleveland Cavaliers | PG | 1999-01-04 | 4764960 |
| 449 | Ricky Rubio | Phoenix Suns | PG | 1990-10-21 | 16200000 |

The two methods default to returning five rows when invoked without an argument:

```
In [28] nba.tail()
```

```
Out [28]
```

| | Name | Team | Position | Birthday | Salary |
|-----|---------------|---------------------|----------|------------|----------|
| 445 | Austin Rivers | Houston Rockets | PG | 1992-08-01 | 2174310 |
| 446 | Harry Giles | Sacramento Kings | PF | 1998-04-22 | 2578800 |
| 447 | Robin Lopez | Milwaukee Bucks | C | 1988-04-01 | 4767000 |
| 448 | Collin Sexton | Cleveland Cavaliers | PG | 1999-01-04 | 4764960 |
| 449 | Ricky Rubio | Phoenix Suns | PG | 1990-10-21 | 16200000 |

The sample method extracts random rows from the DataFrame. Its first parameter specifies the number of rows:

```
In [29] nba.sample(3)
```

```
Out [29]
```

| | Name | Team | Position | Birthday | Salary |
|-----|---------------------|---------------------|----------|------------|----------|
| 225 | Tomas Satoransky | Chicago Bulls | PG | 1991-10-30 | 10000000 |
| 201 | Javonte Green | Boston Celtics | SF | 1993-07-23 | 898310 |
| 310 | Matthew Dellavedova | Cleveland Cavaliers | PG | 1990-09-08 | 9607500 |

Suppose that we want to find out how many teams, salaries, and positions exist in this data set. In chapter 2, we used the `nunique` method to count the number of unique values in a Series. When we invoke the same method on a DataFrame, it returns a Series object with counts of unique values per column:

```
In [30] nba.nunique()
```

```
Out [30] Name      450
        Team       30
        Position     9
        Birthday    430
        Salary      269
        dtype: int64
```

There are 30 unique teams, 269 unique salaries, and 9 unique positions in `nba`.

You may also recall the `max` and `min` methods. On a DataFrame, the `max` method returns a Series with the maximum value from each column. The maximum value in a text column is the string closest to the end of the alphabet. The maximum value in a datetime column is the latest date in chronological order:

```
In [31] nba.max()
```

```
Out [31] Name          Zylan Cheatham
        Team         Washington Wizards
        Position        SG
        Birthday 2000-12-23 00:00:00
        Salary          40231758
        dtype: object
```

The `min` method returns a Series with the minimum value from each column (the smallest number, the string closest to the start of the alphabet, the earliest date, and so on):

```
In [32] nba.min()

Out [32] Name           Aaron Gordon
          Team          Atlanta Hawks
          Position          C
          Birthday   1977-01-26 00:00:00
          Salary            79568
          dtype: object
```

What if we want to identify multiple max values, such as the four highest-paid players in the data set? The `nlargest` method retrieves a subset of rows in which a given column has the largest values in the DataFrame. We pass the number of rows to extract to its `n` parameter and the column to use for sorting to its `columns` parameter. The next example extracts the DataFrame rows that have the four largest values in the `Salary` column:

```
In [33] nba.nlargest(n = 4, columns = "Salary")
```

```
Out [33]
```

| | Name | Team | Position | Birthday | Salary |
|-----|-------------------|-----------------------|----------|------------|----------|
| 205 | Stephen Curry | Golden State Warriors | PG | 1988-03-14 | 40231758 |
| 38 | Chris Paul | Oklahoma City Thunder | PG | 1985-05-06 | 38506482 |
| 219 | Russell Westbrook | Houston Rockets | PG | 1988-11-12 | 38506482 |
| 251 | John Wall | Washington Wizards | PG | 1990-09-06 | 38199000 |

Our next challenge is finding the three oldest players in the league. We can accomplish this task by getting the three earliest dates in the `Birthday` column. The `nsmallest` method can help us; it returns a subset of rows in which a given column has the smallest values in the data set. The smallest datetime values are those that occur earliest in chronological order. Note that the `nlargest` and `nsmallest` methods can be invoked only on numeric or datetime columns:

```
In [34] nba.nsmallest(n = 3, columns = ["Birthday"])
```

```
Out [34]
```

| | Name | Team | Position | Birthday | Salary |
|-----|---------------|-----------------|----------|------------|---------|
| 98 | Vince Carter | Atlanta Hawks | PF | 1977-01-26 | 2564753 |
| 196 | Udonis Haslem | Miami Heat | C | 1980-06-09 | 2564753 |
| 262 | Kyle Korver | Milwaukee Bucks | PF | 1981-03-17 | 6004753 |

What if we want to calculate the sum of all NBA salaries? The DataFrame includes a `sum` method for this purpose:

```
In [35] nba.sum()
```

```
Out [35] Name           Shake MiltonChristian WoodPJ WashingtonDerrick...
          Team          Philadelphia 76ersDetroit PistonsCharlotte Hor...
          Position        SGPFPPFGPFSGSFCSFPGPFCPGSGPFCFPFSGPGSGSF...
          Salary            3444112694
          dtype: object
```

We do get the answer we want, but the output is a bit messy. By default, pandas adds the values in each column. For text columns, the library concatenates all strings into one. To limit the addition to numeric volumes, we can pass `True` to the `sum` method's `numeric_only` parameter:

```
In [36] nba.sum(numeric_only = True)

Out [36] Salary    3444112694
          dtype: int64
```

The total combined salaries of these 450 NBA players is a whopping \$3.4 billion. We can calculate the average salary with the `mean` method. The method accepts the same `numeric_only` parameter to target only numeric columns:

```
In [37] nba.mean(numeric_only = True)

Out [37] Salary    7.653584e+06
          dtype: float64
```

A `DataFrame` also includes methods for statistical calculations such as median, mode, and standard deviation:

```
In [38] nba.median(numeric_only = True)

Out [38] Salary    3303074.5
          dtype: float64

In [39] nba.mode(numeric_only = True)

Out [39]



| <u>Salary</u> |       |
|---------------|-------|
| 0             | 79568 |



In [40] nba.std(numeric_only = True)

Out [40] Salary    9.288810e+06
          dtype: float64
```

For advanced statistical methods, check out the official `Series` documentation (<http://mng.bz/myDa>).

4.3 *Sorting a DataFrame*

Our data set's rows arrived in jumbled, random order, but that's no problem! We can sort a `DataFrame` by one or more columns by using the `sort_values` method.

4.3.1 *Sorting by a single column*

Let's first sort our players in alphabetical order by name. The `sort_values` method's first parameter, `by`, accepts the column that pandas should use to sort the `DataFrame`. Let's pass in the `Name` column as a string:

```
In [41] # The two lines below are equivalent
      nba.sort_values("Name")
      nba.sort_values(by = "Name")
```

Out [41]

| | Name | Team | Position | Birthday | Salary |
|-----|-------------------|-----------------------|----------|------------|----------|
| 52 | Aaron Gordon | Orlando Magic | PF | 1995-09-16 | 19863636 |
| 101 | Aaron Holiday | Indiana Pacers | PG | 1996-09-30 | 2239200 |
| 437 | Abdel Nader | Oklahoma City Thunder | SF | 1993-09-25 | 1618520 |
| 81 | Adam Mokoka | Chicago Bulls | G | 1998-07-18 | 79568 |
| 399 | Admiral Schofield | Washington Wizards | SF | 1997-03-30 | 1000000 |
| ... | ... | ... | ... | ... | ... |
| 159 | Zach LaVine | Chicago Bulls | PG | 1995-03-10 | 19500000 |
| 302 | Zach Norvell | Los Angeles Lakers | SG | 1997-12-09 | 79568 |
| 312 | Zhaire Smith | Philadelphia 76ers | SG | 1999-06-04 | 3058800 |
| 137 | Zion Williamson | New Orleans Pelicans | F | 2000-07-06 | 9757440 |
| 248 | Zylan Cheatham | New Orleans Pelicans | SF | 1995-11-17 | 79568 |

450 rows × 5 columns

The `sort_values` method's `ascending` parameter determines the sort order; it has a default argument of `True`. By default, pandas will sort a column of numbers in increasing order, a column of strings in alphabetical order, and a column of datetimes in chronological order.

If we wanted to sort the names in reverse alphabetical order, we could pass the `ascending` parameter a `False` instead:

```
In [42] nba.sort_values("Name", ascending = False).head()
```

Out [42]

| | Name | Team | Position | Birthday | Salary |
|-----|-----------------|----------------------|----------|------------|----------|
| 248 | Zylan Cheatham | New Orleans Pelicans | SF | 1995-11-17 | 79568 |
| 137 | Zion Williamson | New Orleans Pelicans | F | 2000-07-06 | 9757440 |
| 312 | Zhaire Smith | Philadelphia 76ers | SG | 1999-06-04 | 3058800 |
| 302 | Zach Norvell | Los Angeles Lakers | SG | 1997-12-09 | 79568 |
| 159 | Zach LaVine | Chicago Bulls | PG | 1995-03-10 | 19500000 |

Here's another example: what if we want to find the five youngest players in `nba` without using the `nsmallest` method? We could sort the `Birthday` column in reverse chronological order by using the `sort_values` method with `ascending` set to `False` and then take five rows off the top with the `head` method:

```
In [43] nba.sort_values("Birthday", ascending = False).head()
```

Out [43]

| | Name | Team | Position | Birthday | Salary |
|-----|---------------------|----------------------|----------|------------|---------|
| 136 | Sekou Doumbouya | Detroit Pistons | SF | 2000-12-23 | 3285120 |
| 432 | Talen Horton-Tucker | Los Angeles Lakers | GF | 2000-11-25 | 898310 |
| 137 | Zion Williamson | New Orleans Pelicans | F | 2000-07-06 | 9757440 |
| 313 | RJ Barrett | New York Knicks | SG | 2000-06-14 | 7839960 |
| 392 | Jalen Lecque | Phoenix Suns | G | 2000-06-13 | 898310 |

The youngest player in nba appears first in the output. That player is Sekou Doumbouya, who was born December 23, 2000.

4.3.2 Sorting by multiple columns

We can sort multiple columns in a DataFrame by passing a list to the `sort_values` method's `by` parameter. Pandas will sort the DataFrame's columns consecutively in the order in which they appear in the list. The next example sorts the nba DataFrame first by the Team column and then by the Name column. Pandas defaults to ascending sorts for all columns:

```
In [44] nba.sort_values(by = ["Team", "Name"])
```

```
Out [44]
```

| | Name | Team | Position | Birthday | Salary |
|-----|-----------------|--------------------|----------|------------|----------|
| 359 | Alex Len | Atlanta Hawks | C | 1993-06-16 | 4160000 |
| 167 | Allen Crabbe | Atlanta Hawks | SG | 1992-04-09 | 18500000 |
| 276 | Brandon Goodwin | Atlanta Hawks | PG | 1995-10-02 | 79568 |
| 438 | Bruno Fernando | Atlanta Hawks | C | 1998-08-15 | 1400000 |
| 194 | Cam Reddish | Atlanta Hawks | SF | 1999-09-01 | 4245720 |
| ... | ... | ... | ... | ... | ... |
| 418 | Jordan McRae | Washington Wizards | PG | 1991-03-28 | 1645357 |
| 273 | Justin Robinson | Washington Wizards | PG | 1997-10-12 | 898310 |
| 428 | Moritz Wagner | Washington Wizards | C | 1997-04-26 | 2063520 |
| 21 | Rui Hachimura | Washington Wizards | PF | 1998-02-08 | 4469160 |
| 36 | Thomas Bryant | Washington Wizards | C | 1997-07-31 | 8000000 |

450 rows × 5 columns

Here's how you read the output. The Atlanta Hawks are the first team in the data set when we sort teams by alphabetical order. Within the Atlanta Hawks, Alex Len's name comes first, followed by Allen Crabbe and Brandon Goodwin. Pandas repeats this sorting logic for the remaining teams and names.

We can pass a single Boolean to the `ascending` parameter to apply the same sort order to each column. The next example passes `False`, so pandas first sorts the Team column in descending order and then the Name column in descending order:

```
In [45] nba.sort_values(["Team", "Name"], ascending = False)
```

```
Out [45]
```

| | Name | Team | Position | Birthday | Salary |
|-----|-----------------|--------------------|----------|------------|---------|
| 36 | Thomas Bryant | Washington Wizards | C | 1997-07-31 | 8000000 |
| 21 | Rui Hachimura | Washington Wizards | PF | 1998-02-08 | 4469160 |
| 428 | Moritz Wagner | Washington Wizards | C | 1997-04-26 | 2063520 |
| 273 | Justin Robinson | Washington Wizards | PG | 1997-10-12 | 898310 |
| 418 | Jordan McRae | Washington Wizards | PG | 1991-03-28 | 1645357 |
| ... | ... | ... | ... | ... | ... |
| 194 | Cam Reddish | Atlanta Hawks | SF | 1999-09-01 | 4245720 |
| 438 | Bruno Fernando | Atlanta Hawks | C | 1998-08-15 | 1400000 |

```

276 Brandon Goodwin      Atlanta Hawks      PG 1995-10-02      79568
167 Allen Crabbe         Atlanta Hawks      SG 1992-04-09  18500000
359 Alex Len             Atlanta Hawks      C  1993-06-16   4160000
450 rows × 5 columns

```

What if we want to sort each column in a different order? We might want to sort the teams in ascending order and then sort the salaries within those teams in descending order, for example. To accomplish this task, we can pass the `ascending` parameter a list of Boolean values. The lists passed to the `by` and `ascending` parameters must be equal in length. Pandas will use shared index positions between the two lists to match each column with its associated sort order. In the next example, the `Team` column occupies index position 0 in the `by` list; pandas matches it with the `True` at index position 0 in the `ascending` list, so it sorts the column in ascending order. Pandas applies the same logic to the `Salary` column and sorts it in descending order:

```

In [46] nba.sort_values(
        by = ["Team", "Salary"], ascending = [True, False]
    )

Out [46]

```

| | Name | Team | Position | Birthday | Salary |
|-----|-------------------|--------------------|----------|------------|----------|
| 111 | Chandler Parsons | Atlanta Hawks | SF | 1988-10-25 | 25102512 |
| 28 | Evan Turner | Atlanta Hawks | PG | 1988-10-27 | 18606556 |
| 167 | Allen Crabbe | Atlanta Hawks | SG | 1992-04-09 | 18500000 |
| 213 | De'Andre Hunter | Atlanta Hawks | SF | 1997-12-02 | 7068360 |
| 339 | Jabari Parker | Atlanta Hawks | PF | 1995-03-15 | 6500000 |
| ... | ... | ... | ... | ... | ... |
| 80 | Isaac Bonga | Washington Wizards | PG | 1999-11-08 | 1416852 |
| 399 | Admiral Schofield | Washington Wizards | SF | 1997-03-30 | 1000000 |
| 273 | Justin Robinson | Washington Wizards | PG | 1997-10-12 | 898310 |
| 283 | Garrison Mathews | Washington Wizards | SG | 1996-10-24 | 79568 |
| 353 | Chris Chiozza | Washington Wizards | PG | 1995-11-21 | 79568 |

```
450 rows × 5 columns
```

The data looks good, so let's make our sort permanent. The `sort_values` method supports the `inplace` parameter, but we'll be explicit and reassign the returned `DataFrame` to the `nba` variable (see chapter 3 for a discussion of the imperfections of the `inplace` parameter):

```

In [47] nba = nba.sort_values(
        by = ["Team", "Salary"],
        ascending = [True, False]
    )

```

Hooray—we've sorted our `DataFrame` by the values in the `Team` and `Salary` columns. Now we can figure out which players on each team get paid the most.

4.4 Sorting by index

With our permanent sort, our DataFrame is in a different order from when it arrived:

```
In [48] nba.head()
```

```
Out [48]
```

| | Name | Team | Position | Birthday | Salary |
|-----|------------------|---------------|----------|------------|----------|
| 111 | Chandler Parsons | Atlanta Hawks | SF | 1988-10-25 | 25102512 |
| 28 | Evan Turner | Atlanta Hawks | PG | 1988-10-27 | 18606556 |
| 167 | Allen Crabbe | Atlanta Hawks | SG | 1992-04-09 | 18500000 |
| 213 | De'Andre Hunter | Atlanta Hawks | SF | 1997-12-02 | 7068360 |
| 339 | Jabari Parker | Atlanta Hawks | PF | 1995-03-15 | 6500000 |

How can we return it to its original form?

4.4.1 Sorting by row index

Our nba DataFrame still has its numeric index. If we could sort the data set by index positions rather than by column values, we could return it to its original shape. The `sort_index` method does just that:

```
In [49] # The two lines below are equivalent
nba.sort_index().head()
nba.sort_index(ascending = True).head()
```

```
Out [49]
```

| | Name | Team | Position | Birthday | Salary |
|---|----------------|--------------------|----------|------------|---------|
| 0 | Shake Milton | Philadelphia 76ers | SG | 1996-09-26 | 1445697 |
| 1 | Christian Wood | Detroit Pistons | PF | 1995-09-27 | 1645357 |
| 2 | PJ Washington | Charlotte Hornets | PF | 1998-08-23 | 3831840 |
| 3 | Derrick Rose | Detroit Pistons | PG | 1988-10-04 | 7317074 |
| 4 | Marial Shayok | Philadelphia 76ers | G | 1995-07-26 | 79568 |

We can also reverse the sort order by passing `False` to the method's `ascending` parameter. The next example shows the greatest index positions first:

```
In [50] nba.sort_index(ascending = False).head()
```

```
Out [50]
```

| | Name | Team | Position | Birthday | Salary |
|-----|---------------|---------------------|----------|------------|----------|
| 449 | Ricky Rubio | Phoenix Suns | PG | 1990-10-21 | 16200000 |
| 448 | Collin Sexton | Cleveland Cavaliers | PG | 1999-01-04 | 4764960 |
| 447 | Robin Lopez | Milwaukee Bucks | C | 1988-04-01 | 4767000 |
| 446 | Harry Giles | Sacramento Kings | PF | 1998-04-22 | 2578800 |
| 445 | Austin Rivers | Houston Rockets | PG | 1992-08-01 | 2174310 |

We're back where we started, with the DataFrame sorted by index position. Let's assign this DataFrame back to the `nba` variable:

```
In [51] nba = nba.sort_index()
```

Next up, let's explore how we can sort our `nba` on its other axis.

4.4.2 Sorting by column index

A DataFrame is a two-dimensional data structure. We can sort an additional axis: the vertical axis.

To sort the DataFrame columns in order, we'll again rely on the `sort_index` method. This time, however, we'll need to add an `axis` parameter and pass it an argument of "columns" or 1. The next example sorts the columns in ascending order:

```
In [52] # The two lines below are equivalent
      nba.sort_index(axis = "columns").head()
      nba.sort_index(axis = 1).head()
```

Out [52]

| | Birthday | Name | Position | Salary | Team |
|---|------------|----------------|----------|---------|--------------------|
| 0 | 1996-09-26 | Shake Milton | SG | 1445697 | Philadelphia 76ers |
| 1 | 1995-09-27 | Christian Wood | PF | 1645357 | Detroit Pistons |
| 2 | 1998-08-23 | PJ Washington | PF | 3831840 | Charlotte Hornets |
| 3 | 1988-10-04 | Derrick Rose | PG | 7317074 | Detroit Pistons |
| 4 | 1995-07-26 | Marial Shayok | G | 79568 | Philadelphia 76ers |

How about sorting the columns in reverse alphabetical order? That task is a simple one: we can pass the `ascending` parameter an argument of `False`. The next example invokes the `sort_index` method, targets the columns with the `axis` parameter, and sorts in descending order with the `ascending` parameter:

```
In [53] nba.sort_index(axis = "columns", ascending = False).head()
```

Out [53]

| | Team | Salary | Position | Name | Birthday |
|---|--------------------|---------|----------|----------------|------------|
| 0 | Philadelphia 76ers | 1445697 | SG | Shake Milton | 1996-09-26 |
| 1 | Detroit Pistons | 1645357 | PF | Christian Wood | 1995-09-27 |
| 2 | Charlotte Hornets | 3831840 | PF | PJ Washington | 1998-08-23 |
| 3 | Detroit Pistons | 7317074 | PG | Derrick Rose | 1988-10-04 |
| 4 | Philadelphia 76ers | 79568 | G | Marial Shayok | 1995-07-26 |

Let's take a second to reflect on the power of pandas. With two methods and a few parameters, we were able to sort the DataFrame on both axes, by one column, by multiple columns, in ascending order, in descending order, or in multiple orders. Pandas is remarkably flexible. We only have to combine the right method with the right arguments.

4.5 Setting a new index

At its core, our data set is a collection of players. Therefore, it seems fitting to use the `Name` column's values as the DataFrame's index labels. `Name` also has the benefit of being the only column with unique values.

The `set_index` method returns a new DataFrame with a given column set as the index. Its first parameter, `keys`, accepts the column name as a string:

```
In [54] # The two lines below are equivalent
nba.set_index(keys = "Name")
nba.set_index("Name")

Out [54]
```

| Name | Team | Position | Birthday | Salary |
|----------------|---------------------|----------|------------|----------|
| Shake Milton | Philadelphia 76ers | SG | 1996-09-26 | 1445697 |
| Christian Wood | Detroit Pistons | PF | 1995-09-27 | 1645357 |
| PJ Washington | Charlotte Hornets | PF | 1998-08-23 | 3831840 |
| Derrick Rose | Detroit Pistons | PG | 1988-10-04 | 7317074 |
| Marial Shayok | Philadelphia 76ers | G | 1995-07-26 | 79568 |
| ... | ... | ... | ... | ... |
| Austin Rivers | Houston Rockets | PG | 1992-08-01 | 2174310 |
| Harry Giles | Sacramento Kings | PF | 1998-04-22 | 2578800 |
| Robin Lopez | Milwaukee Bucks | C | 1988-04-01 | 4767000 |
| Collin Sexton | Cleveland Cavaliers | PG | 1999-01-04 | 4764960 |
| Ricky Rubio | Phoenix Suns | PG | 1990-10-21 | 16200000 |

450 rows × 4 columns

Looks good! Let's overwrite our nba variable:

```
In [55] nba = nba.set_index(keys = "Name")
```

As a side note, we can set the index when importing a data set. Pass the column name as a string to the `read_csv` function's `index_col` parameter. The following code leads to the same DataFrame:

```
In [56] nba = pd.read_csv(
        "nba.csv", parse_dates = ["Birthday"], index_col = "Name"
    )
```

Next, we'll talk about selecting rows and columns from our DataFrame.

4.6 Selecting columns and rows from a DataFrame

A DataFrame is a collection of Series objects with a common index. Multiple syntax options are available to extract one or more of these Series from the DataFrame.

4.6.1 Selecting a single column from a DataFrame

Each Series column is available as an attribute on the DataFrame. We use dot syntax to access object attributes. We can extract the Salary column with `nba.Salary`, for example. Notice that the index carries over from the DataFrame to the Series:

```
In [57] nba.Salary

Out [57] Name
      Shake Milton      1445697
      Christian Wood     1645357
      PJ Washington      3831840
```

```
Derrick Rose      7317074
Marial Shayok    79568
...
Austin Rivers    2174310
Harry Giles      2578800
Robin Lopez      4767000
Collin Sexton    4764960
Ricky Rubio      16200000
Name: Salary, Length: 450, dtype: int64
```

We can also extract a column by passing its name in square brackets after the DataFrame:

```
In [58] nba["Position"]

Out [58] Name
Shake Milton      SG
Christian Wood     PF
PJ Washington      PF
Derrick Rose       PG
Marial Shayok      G
...
Austin Rivers      PG
Harry Giles        PF
Robin Lopez        C
Collin Sexton      PG
Ricky Rubio        PG
Name: Position, Length: 450, dtype: object
```

The advantage of the square-bracket syntax is that it supports column names with spaces. If our column was named "Player Position", we could extract it only via square brackets:

```
nba["Player Position"]
```

The attribute syntax would raise an exception. Python has no way of knowing the significance of the space and would assume that we're trying to access a Player column:

```
nba.Player Position
```

Although opinions differ, I recommend using the square-bracket syntax for extraction. I like solutions that work 100% of the time, even if they require typing a few extra characters.

4.6.2 Selecting multiple columns from a DataFrame

To extract multiple DataFrame columns, declare a pair of opening and closing square brackets; then pass the column names in a list. The result will be a new DataFrame whose columns are in the same order as the list elements. The next example targets the Salary and Birthday columns:

```
In [59] nba[["Salary", "Birthday"]]
```

```
Out [59]
```

| Name | Salary | Birthday |
|----------------|---------|------------|
| Shake Milton | 1445697 | 1996-09-26 |
| Christian Wood | 1645357 | 1995-09-27 |
| PJ Washington | 3831840 | 1998-08-23 |
| Derrick Rose | 7317074 | 1988-10-04 |
| Marial Shayok | 79568 | 1995-07-26 |

Pandas will extract the columns based on their order in the list:

```
In [60] nba[["Birthday", "Salary"]].head()
```

```
Out [60]
```

| Name | Birthday | Salary |
|----------------|------------|---------|
| Shake Milton | 1996-09-26 | 1445697 |
| Christian Wood | 1995-09-27 | 1645357 |
| PJ Washington | 1998-08-23 | 3831840 |
| Derrick Rose | 1988-10-04 | 7317074 |
| Marial Shayok | 1995-07-26 | 79568 |

We can use the `select_dtypes` method to select columns based on their data types. The method accepts two parameters, `include` and `exclude`. The parameters accept a single string or a list, representing the column type(s) that pandas should keep or discard. As a reminder, you can access the `dtypes` attribute if you'd like to see each column's datatype. The next example selects only string columns from `nba`:

```
In [61] nba.select_dtypes(include = "object")
```

```
Out [61]
```

| Name | Team | Position |
|----------------|---------------------|----------|
| Shake Milton | Philadelphia 76ers | SG |
| Christian Wood | Detroit Pistons | PF |
| PJ Washington | Charlotte Hornets | PF |
| Derrick Rose | Detroit Pistons | PG |
| Marial Shayok | Philadelphia 76ers | G |
| ... | ... | ... |
| Austin Rivers | Houston Rockets | PG |
| Harry Giles | Sacramento Kings | PF |
| Robin Lopez | Milwaukee Bucks | C |
| Collin Sexton | Cleveland Cavaliers | PG |
| Ricky Rubio | Phoenix Suns | PG |

```
450 rows × 2 columns
```

The next example selects all columns except string and integer columns:

```
In [62] nba.select_dtypes(exclude = ["object", "int"])
```

```
Out [62]
```

| Name | Birthday |
|----------------|------------|
| Shake Milton | 1996-09-26 |
| Christian Wood | 1995-09-27 |
| PJ Washington | 1998-08-23 |
| Derrick Rose | 1988-10-04 |
| Marial Shayok | 1995-07-26 |
| ... | ... |
| Austin Rivers | 1992-08-01 |
| Harry Giles | 1998-04-22 |
| Robin Lopez | 1988-04-01 |
| Collin Sexton | 1999-01-04 |
| Ricky Rubio | 1990-10-21 |

```
450 rows × 1 columns
```

The Birthday column is the only column in nba that holds neither string nor integer values. To include or exclude datetime columns, we can pass an argument of "datetime" to the correct parameter.

4.7 Selecting rows from a DataFrame

Now that we've practiced extracting columns, let's learn how to extract DataFrame rows by index label or position.

4.7.1 Extracting rows by index label

The loc attribute extracts a row by label. We call attributes such as loc *accessors* because they access a piece of data. Type a pair of square brackets immediately after loc and pass in the target index label. The next example extracts the nba row with an index label of "LeBron James". Pandas returns the row's values in a Series. As always, be mindful of case sensitivity:

```
In [63] nba.loc["LeBron James"]
```

```
Out [63] Team           Los Angeles Lakers
          Position        PF
          Birthday      1984-12-30 00:00:00
          Salary         37436858
          Name: LeBron James, dtype: object
```

We can pass a list in between the square brackets to extract multiple rows. When the results set includes multiple records, pandas stores the results in a DataFrame:

```
In [64] nba.loc[["Kawhi Leonard", "Paul George"]]
```

```
Out [64]
```

| Name | Team | Position | Birthday | Salary |
|---------------|----------------------|----------|------------|----------|
| Kawhi Leonard | Los Angeles Clippers | SF | 1991-06-29 | 32742000 |
| Paul George | Los Angeles Clippers | SF | 1990-05-02 | 33005556 |

Pandas organizes the rows in the order in which their index labels appear in the list. The next example swaps the string order from the previous example:

```
In [65] nba.loc[["Paul George", "Kawhi Leonard"]]
```

```
Out [65]
```

| Name | Team | Position | Birthday | Salary |
|---------------|----------------------|----------|------------|----------|
| Paul George | Los Angeles Clippers | SF | 1990-05-02 | 33005556 |
| Kawhi Leonard | Los Angeles Clippers | SF | 1991-06-29 | 32742000 |

We can use loc to extract a sequence of index labels. The syntax mirrors Python's list slicing syntax. We provide the starting value, a colon, and the ending value. For extractions like this one, I strongly recommended sorting the index first, as it accelerates the speed with which pandas finds the value.

Let's say we wanted to target all players between Otto Porter and Patrick Beverley. We can sort the DataFrame index to get the player names in alphabetical order and then provide the two player names to the loc accessor. "Otto Porter" represents our lower bound, and "Patrick Beverley" represents the upper bound:

```
In [66] nba.sort_index().loc["Otto Porter":"Patrick Beverley"]
```

```
Out [66]
```

| Name | Team | Position | Birthday | Salary |
|------------------|----------------------|----------|------------|----------|
| Otto Porter | Chicago Bulls | SF | 1993-06-03 | 27250576 |
| PJ Dozier | Denver Nuggets | PG | 1996-10-25 | 79568 |
| PJ Washington | Charlotte Hornets | PF | 1998-08-23 | 3831840 |
| Pascal Siakam | Toronto Raptors | PF | 1994-04-02 | 2351838 |
| Pat Connaughton | Milwaukee Bucks | SG | 1993-01-06 | 1723050 |
| Patrick Beverley | Los Angeles Clippers | PG | 1988-07-12 | 12345680 |

Note that pandas' loc accessor has some differences with Python's list-slicing syntax. For one, the loc accessor includes the label at the upper bound, whereas Python's list slicing syntax excludes the value at the upper bound.

Here's a quick example to remind you. The next example uses list-slicing syntax to extract the elements from index 0 to index 2 in a list of three elements. Index 2 ("PJ Washington") is exclusive, so Python leaves it out:

```
In [67] players = ["Otto Porter", "PJ Dozier", "PJ Washington"]
players[0:2]
```

```
Out [67] ['Otto Porter', 'PJ Dozier']
```

We can use `loc` to pull rows from the middle of the DataFrame to its end. Pass the square brackets the starting index label and a colon:

```
In [68] nba.sort_index().loc["Zach Collins":]
```

```
Out [68]
```

| Name | | Team | Position | Birthday | Salary |
|-----------------|-------------|--------------------|----------|------------|----------|
| Zach Collins | Portland | Trail Blazers | C | 1997-11-19 | 4240200 |
| Zach LaVine | | Chicago Bulls | PG | 1995-03-10 | 19500000 |
| Zach Norvell | | Los Angeles Lakers | SG | 1997-12-09 | 79568 |
| Zhaire Smith | | Philadelphia 76ers | SG | 1999-06-04 | 3058800 |
| Zion Williamson | New Orleans | Pelicans | F | 2000-07-06 | 9757440 |
| Zylan Cheatham | New Orleans | Pelicans | SF | 1995-11-17 | 79568 |

Turning in the other direction, we can use `loc` slicing to pull rows from the beginning of the DataFrame to a specific index label. Start with a colon and then enter the index label to extract to. The next example returns all players from the start to the data set up to Al Horford:

```
In [69] nba.sort_index().loc[::"Al Horford"]
```

```
Out [69]
```

| Name | | Team | Position | Birthday | Salary |
|-------------------|---------------|----------------|----------|------------|----------|
| Aaron Gordon | | Orlando Magic | PF | 1995-09-16 | 19863636 |
| Aaron Holiday | | Indiana Pacers | PG | 1996-09-30 | 2239200 |
| Abdel Nader | Oklahoma City | Thunder | SF | 1993-09-25 | 1618520 |
| Adam Mokoka | | Chicago Bulls | G | 1998-07-18 | 79568 |
| Admiral Schofield | Washington | Wizards | SF | 1997-03-30 | 1000000 |
| Al Horford | Philadelphia | 76ers | C | 1986-06-03 | 28000000 |

Pandas will raise an exception if the index label does not exist in the DataFrame:

```
In [70] nba.loc["Bugs Bunny"]
```

```
KeyError
```

```
Traceback (most recent call last)
```

```
KeyError: 'Bugs Bunny'
```

As its name suggests, the `KeyError` exception communicates that a key does not exist in a given data structure.

4.7.2 Extracting rows by index position

The `iloc` (index location) accessor extracts rows by index position, which is helpful when the position of our rows has significance in our data set. The syntax is similar to the one we used for `loc`. Enter a pair of square brackets after `iloc`, and pass in an integer. Pandas will extract the row at that index:

```
In [71] nba.iloc[300]
```

```
Out [71] Team           Denver Nuggets
          Position        PF
          Birthday   1999-04-03 00:00:00
          Salary            1416852
          Name: Jarred Vanderbilt, dtype: object
```

The `iloc` accessor also accepts a list of index positions to target multiple records. The next example pulls out the players at index positions 100, 200, 300, and 400:

```
In [72] nba.iloc[[100, 200, 300, 400]]
```

```
Out [72]
```

| Name | Team | Position | Birthday | Salary |
|-------------------|-------------------|----------|------------|---------|
| Brian Bowen | Indiana Pacers | SG | 1998-10-02 | 79568 |
| Marco Belinelli | San Antonio Spurs | SF | 1986-03-25 | 5846154 |
| Jarred Vanderbilt | Denver Nuggets | PF | 1999-04-03 | 1416852 |
| Louis King | Detroit Pistons | F | 1999-04-06 | 79568 |

We can use list-slicing syntax with the `iloc` accessor as well. Note, however, that pandas excludes the index position after the colon. The next example passes a slice of `400:404`. Pandas includes the rows at index positions 400, 401, 402, and 403, and excludes the row at index 404:

```
In [73] nba.iloc[400:404]
```

```
Out [73]
```

| Name | Team | Position | Birthday | Salary |
|----------------------|--------------------|----------|------------|----------|
| Louis King | Detroit Pistons | F | 1999-04-06 | 79568 |
| Kostas Antetokounmpo | Los Angeles Lakers | PF | 1997-11-20 | 79568 |
| Rodions Kurucs | Brooklyn Nets | PF | 1998-02-05 | 1699236 |
| Spencer Dinwiddie | Brooklyn Nets | PG | 1993-04-06 | 10605600 |

We can leave out the number before the colon to pull from the start of the DataFrame. Here, we target rows from the beginning of `nba` up to (but not including) index position 2:

```
In [74] nba.iloc[:2]
```

```
Out [74]
```

| Name | Team | Position | Birthday | Salary |
|----------------|--------------------|----------|------------|---------|
| Shake Milton | Philadelphia 76ers | SG | 1996-09-26 | 1445697 |
| Christian Wood | Detroit Pistons | PF | 1995-09-27 | 1645357 |

Similarly, we can remove the number after the colon to pull to the end of the DataFrame. Here, we target the rows from index position 447 to the end of `nba`:

```
In [75] nba.iloc[447:]
```

```
Out [75]
```

| Name | Team | Position | Birthday | Salary |
|---------------|---------------------|----------|------------|----------|
| Robin Lopez | Milwaukee Bucks | C | 1988-04-01 | 4767000 |
| Collin Sexton | Cleveland Cavaliers | PG | 1999-01-04 | 4764960 |
| Ricky Rubio | Phoenix Suns | PG | 1990-10-21 | 16200000 |

We can also pass negative numbers for either value or both values. The next example extracts rows from the 10th-to-last row up to (but not including) the sixth-to-last row:

```
In [76] nba.iloc[-10:-6]
```

```
Out [76]
```

| Name | Team | Position | Birthday | Salary |
|-------------------|-----------------------|----------|------------|---------|
| Jared Dudley | Los Angeles Lakers | PF | 1985-07-10 | 2564753 |
| Max Strus | Chicago Bulls | SG | 1996-03-28 | 79568 |
| Kevon Looney | Golden State Warriors | C | 1996-02-06 | 4464286 |
| Willy Hernangomez | Charlotte Hornets | C | 1994-05-27 | 1557250 |

We can provide a third number inside the square brackets to create the step sequence, a gap between every two index positions. The next example pulls the first 10 nba rows in increments of 2. The resulting DataFrame includes the rows with index positions 0, 2, 4, 6, and 8:

```
In [77] nba.iloc[0:10:2]
```

```
Out [77]
```

| Name | Team | Position | Birthday | Salary |
|---------------|--------------------|----------|------------|----------|
| Shake Milton | Philadelphia 76ers | SG | 1996-09-26 | 1445697 |
| PJ Washington | Charlotte Hornets | PF | 1998-08-23 | 3831840 |
| Marial Shayok | Philadelphia 76ers | G | 1995-07-26 | 79568 |
| Kendrick Nunn | Miami Heat | SG | 1995-08-03 | 1416852 |
| Brook Lopez | Milwaukee Bucks | C | 1988-04-01 | 12093024 |

This slicing technique is particularly effective when we want to pull out every other row.

4.7.3 Extracting values from specific columns

Both the loc and iloc attributes accept a second argument representing the column(s) to extract. If we're using loc, we have to provide the column name. If we're using iloc, we have to provide the column position. The next example uses loc to pull the value at the intersection of the "Giannis Antetokounmpo" row and the Team column:

```
In [78] nba.loc["Giannis Antetokounmpo", "Team"]
```

```
Out [78] 'Milwaukee Bucks'
```

To specify multiple values, we can pass a list for one or both of the arguments to the `loc` accessor. The next example extracts the row with a "James Harden" index label and the values from the Position and Birthday columns. Pandas returns a `Series`:

```
In [79] nba.loc["James Harden", ["Position", "Birthday"]]

Out [79] Position          PG
         Birthday   1989-08-26 00:00:00
         Name: James Harden, dtype: object
```

The next example provides multiple row labels and multiple columns:

```
In [80] nba.loc[
        ["Russell Westbrook", "Anthony Davis"],
        ["Team", "Salary"]
    ]

Out [80]
      Team      Salary
Name
Russell Westbrook  Houston Rockets  38506482
Anthony Davis       Los Angeles Lakers  27093019
```

We can also use list-slicing syntax to extract multiple columns without explicitly writing out their names. We have four columns in our data set (Team, Position, Birthday, and Salary). Let's extract all columns from Position to Salary. Pandas includes both endpoints in a `loc` slice:

```
In [81] nba.loc["Joel Embiid", "Position": "Salary"]

Out [81] Position          C
         Birthday   1994-03-16 00:00:00
         Salary      27504630
         Name: Joel Embiid, dtype: object
```

We must pass the column names in the order in which they appear in the `DataFrame`. The next example yields an empty result because the `Salary` column comes after the `Position` column. Pandas is unable to identify which columns to pull out:

```
In [82] nba.loc["Joel Embiid", "Salary": "Position"]

Out [82] Series([], Name: Joel Embiid, dtype: object)
```

Let's say we wanted to target columns by their order rather than by their name. Remember that pandas assigns an index position to each `DataFrame` column. In `nba`, the `Team` column has an index of 0, `Position` has an index of 1, and so on. We can pass a column's index as the second argument to `iloc`. The next example targets the value at the intersection of the row at index 57 and the column at index 3 (`Salary`):

```
In [83] nba.iloc[57, 3]

Out [83] 796806
```

We can use list-slicing syntax here as well. The next example pulls all rows from index position 100 up to but not including index position 104. It also includes all columns from the beginning of the columns up to but not including the column at index position 3 (Salary):

```
In [84] nba.iloc[100:104, :3]
```

```
Out [84]
```

| Name | Team | Position | Birthday |
|---------------|--------------------|----------|------------|
| Brian Bowen | Indiana Pacers | SG | 1998-10-02 |
| Aaron Holiday | Indiana Pacers | PG | 1996-09-30 |
| Troy Daniels | Los Angeles Lakers | SG | 1991-07-15 |
| Buddy Hield | Sacramento Kings | SG | 1992-12-17 |

The `iloc` and `loc` accessors are remarkably versatile. Their square brackets can accept a single value, a list of values, a list slice, and more. The disadvantage of this flexibility is that it demands extra overhead; pandas has to figure out what kind of input we've given to `iloc` or `loc`.

We can use two alternative attributes, `at` and `iat`, when we know that we want to extract a single value from a DataFrame. The two attributes are speedier because pandas can optimize its searching algorithms when looking for a single value.

The syntax is similar. The `at` attribute accepts row and column labels:

```
In [85] nba.at["Austin Rivers", "Birthday"]
```

```
Out [85] Timestamp('1992-08-01 00:00:00')
```

The `iat` attribute accepts row and column indices:

```
In [86] nba.iat[263, 1]
```

```
Out [86] 'PF'
```

Jupyter Notebook includes several magic methods to help enhance our developer experience. We declare magic methods with a `%%` prefix and enter them alongside our regular Python code. One example is `%%timeit`, which runs the code in a cell and calculates the average time it takes to execute. `%%timeit` sometimes runs the cell up to 100,000 times! The next examples use the magic method to compare the speed of the accessors we've explored so far:

```
In [87] %%timeit
        nba.at["Austin Rivers", "Birthday"]
```

```
6.38 µs ± 53.6 ns per loop (mean ± std. dev. of 7 runs, 100000 loops each)
```

```
In [88] %%timeit
        nba.loc["Austin Rivers", "Birthday"]
```

```
9.12 µs ± 53.8 ns per loop (mean ± std. dev. of 7 runs, 100000 loops each)
```

```
In [89] %%timeit
      nba.iat[263, 1]

4.7 µs ± 27.4 ns per loop (mean ± std. dev. of 7 runs, 100000 loops each)

In [90] %%timeit
      nba.iloc[263, 1]

7.41 µs ± 39.1 ns per loop (mean ± std. dev. of 7 runs, 100000 loops each)
```

The results are subject to some variance between different computers but show the clear speed advantage of at and iat over loc and iloc.

4.8 Extracting values from Series

The loc, iloc, at, and iat accessors are available on Series objects as well. We can practice on a sample Series from our DataFrame, such as Salary:

```
In [91] nba["Salary"].loc["Damian Lillard"]

Out [91] 29802321

In [92] nba["Salary"].at["Damian Lillard"]

Out [92] 29802321

In [93] nba["Salary"].iloc[234]

Out [93] 2033160

In [94] nba["Salary"].iat[234]

Out [94] 2033160
```

Feel free to use whatever accessors work best for you.

4.9 Renaming columns or rows

Do you recall the columns attribute? It exposes the Index object that stores the DataFrame's column names:

```
In [95] nba.columns

Out [95] Index(['Team', 'Position', 'Birthday', 'Salary'], dtype='object')
```

We can rename any or all of a DataFrame's columns by assigning a list of new names to the attribute. The next example changes the name of the Salary column to Pay:

```
In [96] nba.columns = ["Team", "Position", "Date of Birth", "Pay"]
      nba.head(1)

Out [96]
```

| Name | Team | Position | Date of Birth | Pay |
|--------------|--------------------|----------|---------------|---------|
| Shake Milton | Philadelphia 76ers | SG | 1996-09-26 | 1445697 |

The `rename` method is an alternative option that accomplishes the same result. We can pass to its `columns` parameter a dictionary in which the keys are the existing column names and the values are their new names. The next example alters the Date of Birth column's name to Birthday:

```
In [97] nba.rename(columns = { "Date of Birth": "Birthday" })
```

```
Out [97]
```

| Name | Team | Position | Birthday | Pay |
|----------------|---------------------|----------|------------|----------|
| Shake Milton | Philadelphia 76ers | SG | 1996-09-26 | 1445697 |
| Christian Wood | Detroit Pistons | PF | 1995-09-27 | 1645357 |
| PJ Washington | Charlotte Hornets | PF | 1998-08-23 | 3831840 |
| Derrick Rose | Detroit Pistons | PG | 1988-10-04 | 7317074 |
| Marial Shayok | Philadelphia 76ers | G | 1995-07-26 | 79568 |
| ... | ... | ... | ... | ... |
| Austin Rivers | Houston Rockets | PG | 1992-08-01 | 2174310 |
| Harry Giles | Sacramento Kings | PF | 1998-04-22 | 2578800 |
| Robin Lopez | Milwaukee Bucks | C | 1988-04-01 | 4767000 |
| Collin Sexton | Cleveland Cavaliers | PG | 1999-01-04 | 4764960 |
| Ricky Rubio | Phoenix Suns | PG | 1990-10-21 | 16200000 |

```
450 rows × 4 columns
```

Let's make the operation permanent by assigning the returned DataFrame to the `nba` variable:

```
In [98] nba = nba.rename(columns = { "Date of Birth": "Birthday" })
```

We can also rename index labels by passing a dictionary to the method's `index` parameter. The same logic applies; the keys are the old labels, and the values are the new ones. The following example swaps "Giannis Antetokounmpo" with his popular nickname "Greek Freak":

```
In [99] nba.loc["Giannis Antetokounmpo"]
```

```
Out [99] Team           Milwaukee Bucks
          Position        PF
          Birthday       1994-12-06 00:00:00
          Pay            25842697
```

```
Name: Giannis Antetokounmpo, dtype: object
```

```
In [100] nba = nba.rename(
          index = { "Giannis Antetokounmpo": "Greek Freak" }
        )
```

Let's try looking up the row by its new label:

```
In [101] nba.loc["Greek Freak"]
```

```
Out [101] Team           Milwaukee Bucks
          Position        PF
          Birthday       1994-12-06 00:00:00
          Pay            25842697
Name: Greek Freak, dtype: object
```

We've successfully changed the row label!

4.10 Resetting an index

Sometimes, we want to set another column as the index of our DataFrame. Let's say we wanted to make Team the index of nba. We could invoke the `set_index` method we introduced earlier in the chapter with a different column, but we would lose our current index of player names. Take a look at this example:

```
In [102] nba.set_index("Team").head()
```

```
Out [102]
```

| Team | Position | Birthday | Salary |
|--------------------|----------|------------|---------|
| Philadelphia 76ers | SG | 1996-09-26 | 1445697 |
| Detroit Pistons | PF | 1995-09-27 | 1645357 |
| Charlotte Hornets | PF | 1998-08-23 | 3831840 |
| Detroit Pistons | PG | 1988-10-04 | 7317074 |
| Philadelphia 76ers | G | 1995-07-26 | 79568 |

To preserve the players' names, we must first reintegrate the existing index as a regular column in the DataFrame. The `reset_index` method moves the current index to a DataFrame column and replaces the former index with pandas' numeric index:

```
In [103] nba.reset_index().head()
```

```
Out [103]
```

| | Name | Team | Position | Birthday | Salary |
|---|----------------|--------------------|----------|------------|---------|
| 0 | Shake Milton | Philadelphia 76ers | SG | 1996-09-26 | 1445697 |
| 1 | Christian Wood | Detroit Pistons | PF | 1995-09-27 | 1645357 |
| 2 | PJ Washington | Charlotte Hornets | PF | 1998-08-23 | 3831840 |
| 3 | Derrick Rose | Detroit Pistons | PG | 1988-10-04 | 7317074 |
| 4 | Marial Shayok | Philadelphia 76ers | G | 1995-07-26 | 79568 |

Now we can use the `set_index` method to move the Team column to the index with no data loss:

```
In [104] nba.reset_index().set_index("Team").head()
```

```
Out [104]
```

| Team | Name | Position | Birthday | Salary |
|--------------------|----------------|----------|------------|---------|
| Philadelphia 76ers | Shake Milton | SG | 1996-09-26 | 1445697 |
| Detroit Pistons | Christian Wood | PF | 1995-09-27 | 1645357 |
| Charlotte Hornets | PJ Washington | PF | 1998-08-23 | 3831840 |
| Detroit Pistons | Derrick Rose | PG | 1988-10-04 | 7317074 |
| Philadelphia 76ers | Marial Shayok | G | 1995-07-26 | 79568 |

One advantage of avoiding the `inplace` parameter is that we can chain multiple method calls. Let's chain the `reset_index` and `set_index` method calls and overwrite the `nba` variable with the result:

```
In [105] nba = nba.reset_index().set_index("Team")
```

That's all there is to cover. You're now acquainted with the `DataFrame`, the core workhorse of the pandas library.

4.11 Coding challenge

Now that we've explored the NBA's financials, let's apply the chapter's concepts in a different sports league.

4.11.1 Problems

The `nfl.csv` file contains a list of players in the National Football League with similar Name, Team, Position, Birthday, and Salary columns. See whether you can answer these questions:

- 1 How can we import the `nfl.csv` file? What's an effective way to convert the values in its `Birthday` column to datetimes?
- 2 What are the two ways we can set the `DataFrame` index to store the player names?
- 3 How can we count the number of players per team in this data set?
- 4 Who are the five highest-paid players?
- 5 How can we sort the data set first by teams in alphabetical order and then by salary in descending order?
- 6 Who is the oldest player on the New York Jets roster, and what is his birthday?

4.11.2 Solutions

Let's walk through the challenges step by step:

- 1 We can import the CSV with the `read_csv` function. To store the `Birthday` column values as datetimes, we'll pass the column to the `parse_dates` parameter in a list:

```
In [106]: nfl = pd.read_csv("nfl.csv", parse_dates = ["Birthday"])
          nfl
```

```
Out [106]
```

| | Name | Team | Position | Birthday | Salary |
|-----------------------|-------------------|----------------------|----------|------------|---------|
| 0 | Tremon Smith | Philadelphia Eagles | RB | 1996-07-20 | 570000 |
| 1 | Shawn Williams | Cincinnati Bengals | SS | 1991-05-13 | 3500000 |
| 2 | Adam Butler | New England Patriots | DT | 1994-04-12 | 645000 |
| 3 | Derek Wolfe | Denver Broncos | DE | 1990-02-24 | 8000000 |
| 4 | Jake Ryan | Jacksonville Jaguars | OLB | 1992-02-27 | 1000000 |
| .. | .. | .. | .. | .. | .. |
| 1650 | Bashaud Breeland | Kansas City Chiefs | CB | 1992-01-30 | 805000 |
| 1651 | Craig James | Philadelphia Eagles | CB | 1996-04-29 | 570000 |
| 1652 | Jonothan Harrison | New York Jets | C | 1991-08-25 | 1500000 |
| 1653 | Chuma Edoga | New York Jets | OT | 1997-05-25 | 495000 |
| 1654 | Tajae Sharpe | Tennessee Titans | WR | 1994-12-23 | 2025000 |
| 1655 rows × 5 columns | | | | | |

- 2 Our next challenge is setting the player names as the index labels. Our option is to invoke the `set_index` method and assign the new DataFrame to the `nfl` variable:

```
In [107] nfl = nfl.set_index("Name")
```

Another option is to provide the `index_col` parameter to the `read_csv` function when importing the data set:

```
In [108] nfl = pd.read_csv(
    "nfl.csv", index_col = "Name", parse_dates = ["Birthday"])
)
```

The result will be the same either way:

```
In [109] nfl.head()
```

```
Out [109]
```

| Name | Team | Position | Birthday | Salary |
|----------------|----------------------|----------|------------|---------|
| Tremon Smith | Philadelphia Eagles | RB | 1996-07-20 | 570000 |
| Shawn Williams | Cincinnati Bengals | SS | 1991-05-13 | 3500000 |
| Adam Butler | New England Patriots | DT | 1994-04-12 | 645000 |
| Derek Wolfe | Denver Broncos | DE | 1990-02-24 | 8000000 |
| Jake Ryan | Jacksonville Jaguars | OLB | 1992-02-27 | 1000000 |

- 3 To count the number of players per team, we can invoke the `value_counts` method on the Team column. First, we need to extract the Team Series with dot syntax or square brackets:

```
In [110] # The two lines below are equivalent
nfl.Team.value_counts().head()
nfl["Team"].value_counts().head()
```

```
Out [110] New York Jets      58
          Washington Redskins  56
          Kansas City Chiefs   56
          San Francisco 49Ers   55
          New Orleans Saints   55
```

- 4 To identify the five highest-paid players, we can use the `sort_values` method to sort the Salary column. To tell pandas to sort in descending order, we can pass the `ascending` parameter an argument of `False`. Another option is the `nlargest` method:

```
In [111] nfl.sort_values("Salary", ascending = False).head()
```

```
Out [111]
```

| Name | Team | Position | Birthday | Salary |
|----------------|----------------------|----------|------------|----------|
| Kirk Cousins | Minnesota Vikings | QB | 1988-08-19 | 27500000 |
| Jameis Winston | Tampa Bay Buccaneers | QB | 1994-01-06 | 20922000 |

| | | | | |
|-----------------|---------------------|----|------------|----------|
| Marcus Mariota | Tennessee Titans | QB | 1993-10-30 | 20922000 |
| Derek Carr | Oakland Raiders | QB | 1991-03-28 | 19900000 |
| Jimmy Garoppolo | San Francisco 49Ers | QB | 1991-11-02 | 17200000 |

- 5 To sort by multiple columns, we'll have to pass arguments to both the `by` and `ascending` parameters of the `sort_values` method. The following code sorts the `Team` column in ascending order followed by the `Salary` column in descending order:

```
In [112] nfl.sort_values(
    by = ["Team", "Salary"],
    ascending = [True, False]
)
```

Out [112]

| Name | | Team | Position | Birthday | Salary |
|--------------------|---------------------|------|------------|----------|--------|
| Chandler Jones | Arizona Cardinals | OLB | 1990-02-27 | 16500000 | |
| Patrick Peterson | Arizona Cardinals | CB | 1990-07-11 | 11000000 | |
| Larry Fitzgerald | Arizona Cardinals | WR | 1983-08-31 | 11000000 | |
| David Johnson | Arizona Cardinals | RB | 1991-12-16 | 5700000 | |
| Justin Pugh | Arizona Cardinals | G | 1990-08-15 | 5000000 | |
| ... | ... | ... | ... | ... | ... |
| Ross Pierschbacher | Washington Redskins | C | 1995-05-05 | 495000 | |
| Kelvin Harmon | Washington Redskins | WR | 1996-12-15 | 495000 | |
| Wes Martin | Washington Redskins | G | 1996-05-09 | 495000 | |
| Jimmy Moreland | Washington Redskins | CB | 1995-08-26 | 495000 | |
| Jeremy Reaves | Washington Redskins | SS | 1996-08-29 | 495000 | |

1655 rows × 4 columns

- 6 The final challenge is a tricky one: we have to find the oldest player on the New York Jets roster. Given the current tools at our disposal, we can set the `Team` column as the `DataFrame` index to allow for easy extraction of all Jets players. To preserve the player names currently in our index, we'll first use the `reset_index` method to move them back into the `DataFrame` as a regular column:

```
In [113] nfl = nfl.reset_index().set_index(keys = "Team")
nfl.head(3)
```

Out [113]

| Team | | Name | Position | Birthday | Salary |
|----------------------|----------------|------|------------|----------|--------|
| Philadelphia Eagles | Tremon Smith | RB | 1996-07-20 | 570000 | |
| Cincinnati Bengals | Shawn Williams | SS | 1991-05-13 | 3500000 | |
| New England Patriots | Adam Butler | DT | 1994-04-12 | 645000 | |

Next, we can use the `loc` attribute to isolate all players on the New York Jets:

```
In [114] nfl.loc["New York Jets"].head()
```

Out [114]

| Team | Name | Position | Birthday | Salary |
|---------------|------------------|----------|------------|---------|
| New York Jets | Bronson Kaufusi | DE | 1991-07-06 | 645000 |
| New York Jets | Darryl Roberts | CB | 1990-11-26 | 1000000 |
| New York Jets | Jordan Willis | DE | 1995-05-02 | 754750 |
| New York Jets | Quinnen Williams | DE | 1997-12-21 | 495000 |
| New York Jets | Sam Ficken | K | 1992-12-14 | 495000 |

The last step is to sort the Birthday column and extract the top record. This sort is possible only because we converted the column's values to datetimes:

```
In [115] nfl.loc["New York Jets"].sort_values("Birthday").head(1)

Out [115]
```

| Team | Name | Position | Birthday | Salary |
|---------------|------------|----------|------------|---------|
| New York Jets | Ryan Kalil | C | 1985-03-29 | 2400000 |

The oldest player on the New York Jets in this data set is Ryan Kalil. His birthday was March 29, 1985.

Congratulations on completing the coding challenge!

Summary

- The DataFrame is a two-dimensional data structure consisting of rows and columns.
- The DataFrame shares attributes and methods with the Series. Many of the attributes and methods operate differently due to the dimensional differences between the two objects.
- The sort_values method sorts one or more DataFrame columns. We can assign each column a different sort order (ascending or descending).
- The loc attribute extracts rows or columns by index label. The at attribute is a convenient shortcut for targeting only one value.
- The iloc attribute extracts rows or columns by index position. The iat attribute is a convenient shortcut for targeting only one value.
- The reset_index method restores an index as a regular column in the DataFrame.
- The rename method sets a different name for one or more columns or rows.

5

Filtering a DataFrame

This chapter covers

- Reducing a DataFrame's memory use
- Extracting DataFrame rows by one or more conditions
- Filtering a DataFrame for rows that include or exclude null values
- Selecting column values that fall between a range
- Removing duplicate and null values from a DataFrame

In chapter 4, we learned how to extract rows, columns, and cell values from a DataFrame by using the `loc` and `iloc` accessors. These accessors work well when we know the index labels and positions of the rows/columns we want to target. Sometimes, we may want to target rows not by an identifier but by a condition or a criterion. We may want to extract a subset of rows in which a column holds a specific value, for example.

In this chapter, we'll learn how to declare logical conditions that include and exclude rows from a DataFrame. We'll see how to combine multiple conditions by using AND and OR logic. Finally, we'll introduce some pandas utility methods that simplify the filtering process. Lots of fun lies ahead, so let's jump in.

5.1 Optimizing a data set for memory use

Before we segue into filtering, let's quickly talk about reducing memory in pandas. Whenever importing a data set, it's important to consider whether each column stores its data in the most optimal type. The "best" data type is the one that consumes the least memory or provides the most utility. Integers occupy less memory than floating-point numbers on most computers, for example, so if your data set includes whole numbers, it's ideal to import them as integers rather than floating-points. As another example, if your data set includes dates, it's ideal to import them as datetimes rather than as strings, which allows for datetime-specific operations. In this section, we'll learn some tips and tricks to shrink memory consumption by converting column data to different types, which will facilitate faster filtering later. Let's begin with the usual import of our favorite data analysis library:

```
In [1] import pandas as pd
```

This chapter's employees.csv data set is a fictional collection of workers at a company. Each record includes the employee's first name, gender, start date at the firm, salary, manager status (True or False), and team. Let's take a peek at the data set with the `read_csv` function:

```
In [2] pd.read_csv("employees.csv")
```

```
Out [2]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|------|------------|--------|------------|----------|-------|--------------|
| 0 | Douglas | Male | 8/6/93 | NaN | True | Marketing |
| 1 | Thomas | Male | 3/31/96 | 61933.0 | True | NaN |
| 2 | Maria | Female | NaN | 130590.0 | False | Finance |
| 3 | Jerry | NaN | 3/4/05 | 138705.0 | True | Finance |
| 4 | Larry | Male | 1/24/98 | 101004.0 | True | IT |
| ... | ... | ... | ... | ... | ... | ... |
| 996 | Phillip | Male | 1/31/84 | 42392.0 | False | Finance |
| 997 | Russell | Male | 5/20/13 | 96914.0 | False | Product |
| 998 | Larry | Male | 4/20/13 | 60500.0 | False | Business Dev |
| 999 | Albert | Male | 5/15/12 | 129949.0 | True | Sales |
| 1000 | NaN | NaN | NaN | NaN | NaN | NaN |

```
1001 rows × 6 columns
```

Take a second to notice the NaNs scattered throughout the output. Every column has missing values. In fact, the last row consists only of NaNs. Imperfect data like this is common in the real world. Data sets can arrive with blank rows, blank columns, and more.

How can we increase the utility of our data set? Our first optimization is one that we should feel comfortable with by now. We can convert the text values in the Start Date column to datetimes with the `parse_dates` parameter:

```
In [3] pd.read_csv("employees.csv", parse_dates = ["Start Date"]).head()
```

```
Out [3]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|---|-------------------|---------------|-------------------|---------------|-------------|-------------|
| 0 | Douglas | Male | 1993-08-06 | NaN | True | Marketing |
| 1 | Thomas | Male | 1996-03-31 | 61933.0 | True | NaN |
| 2 | Maria | Female | | NaT | 130590.0 | False |
| 3 | Jerry | Nan | 2005-03-04 | 138705.0 | True | Finance |
| 4 | Larry | Male | 1998-01-24 | 101004.0 | True | IT |

We're in a good place with the CSV import, so let's assign the `DataFrame` object to a descriptive variable such as `employees`:

```
In [4] employees = pd.read_csv(
    "employees.csv", parse_dates = ["Start Date"]
)
```

A few options are available for improving the speed and efficiency of `DataFrame` operations. First, let's summarize the data set as it currently stands. We can invoke the `info` method to see a list of the columns, their data types, a count of missing values, and the `DataFrame`'s total memory consumption:

```
In [5] employees.info()
```

```
Out [5]
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1001 entries, 0 to 1000
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype  
 ---  --          --          --    
 0   First Name  933 non-null   object  
 1   Gender       854 non-null   object  
 2   Start Date  999 non-null   datetime64[ns]
 3   Salary       999 non-null   float64 
 4   Mgmt        933 non-null   object  
 5   Team         957 non-null   object  
dtypes: datetime64[ns](1), float64(1), object(4)
message usage: 47.0+ KB
```

Let's walk through the output from top to bottom. We have a `DataFrame` with 1,001 rows, starting at index 0 and proceeding to index 1000. There are four string columns, one datetime column, and one floating-point column. All six columns have missing data.

Memory use currently is ~47 KB—a small amount for modern computers, but let's try to whittle the number down. As you read the following examples, focus more on

the percentage reductions than on the numeric reductions. The larger your data sets grow, the more significant the performance improvement will be.

5.1.1 **Converting data types with the astype method**

Did you notice that pandas imported the Mgmt column's values as strings? The column stores only two values: True and False. We can reduce memory use by converting the values to the more lightweight Boolean data type.

The astype method converts a Series' values to a different data type. It accepts a single argument: the new data type. We can pass either the data type or a string with its name.

The next example extracts the Mgmt Series from employees and invokes its astype method with an argument of bool. Pandas returns a new Series object of Booleans. Note that the library converts NaNs to True values. We'll discuss removing missing values in section 5.5.4.

```
In [6] employees["Mgmt"].astype(bool)

Out [6] 0      True
        1      True
        2     False
        3      True
        4      True
        ...
       996    False
       997    False
       998    False
       999    True
      1000   True
Name: Mgmt, Length: 1001, dtype: bool
```

Looks good! Now that we've previewed what the Series will look like, we can overwrite the existing Mgmt column in employees. Updating a DataFrame column works similarly to setting a key-value pair in a dictionary. If a column with the specified name exists, pandas overwrites it with the new Series. If the column with the name does not exist, pandas creates a new Series and appends it to the right of the DataFrame. The library matches rows in the Series and DataFrame by shared index labels.

The next code sample overwrites the Mgmt column with our new Series of Booleans. As a reminder, Python evaluates the right side of the assignment operator (=) first. First, we create a new Series, then we overwrite our existing Mgmt column:

```
In [7] employees["Mgmt"] = employees["Mgmt"].astype(bool)
```

A column assignment does not produce a return value, so the code does not output anything in Jupyter Notebook. Let's take a look at the DataFrame again to see the results:

```
In [8] employees.tail()
```

```
Out [8]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|------|------------|--------|------------|----------|-------|--------------|
| 996 | Phillip | Male | 1984-01-31 | 42392.0 | False | Finance |
| 997 | Russell | Male | 2013-05-20 | 96914.0 | False | Product |
| 998 | Larry | Male | 2013-04-20 | 60500.0 | False | Business Dev |
| 999 | Albert | Male | 2012-05-15 | 129949.0 | True | Sales |
| 1000 | NaN | NaN | NaT | NaN | True | NaN |

Except for the True in the last row of missing values, the DataFrame looks no different. But what about our memory use? Let's invoke the `info` method again to see the difference:

```
In [9] employees.info()
```

```
Out [9]
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1001 entries, 0 to 1000
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype  
 ---  --          --          --      
 0   First Name  933 non-null    object 
 1   Gender       854 non-null    object 
 2   Start Date  999 non-null    datetime64[ns]
 3   Salary       999 non-null    float64
 4   Mgmt         1001 non-null   bool    
 5   Team         957 non-null    object 
dtypes: bool(1), datetime64[ns](1), float64(1), object(3)
memory usage: 40.2+ KB
```

We've reduced `employees`' memory use by almost 15%, from 47 KB to 40.2 KB. That's a pretty good start!

Next, let's transition to the `Salary` column. If we open the raw CSV file, we can see that its values are stored as whole numbers:

```
First Name,Gender,Start Date,Salary,Mgmt,Team
Douglas,Male,8/6/93,,True,Marketing
Thomas,Male,3/31/96,61933,True,
Maria,Female,,130590,False,Finance
Jerry,,3/4/05,138705,True,Finance
```

In `employees`, however, pandas stores the `Salary` values as floats. To support the NaNs throughout the column, pandas converts the integers to floating-point numbers—a technical requirement of the library that we observed in earlier chapters.

Following our previous Boolean example, we might try to coerce the column's values to integers with the `astype` method. Unfortunately, pandas raises a `ValueError` exception:

```
In [10] employees["Salary"].astype(int)

-----
ValueError                                Traceback (most recent call last)
<ipython-input-99-b148c8b8be90> in <module>
----> 1 employees["Salary"].astype(int)

ValueError: Cannot convert non-finite values (NA or inf) to integer
```

Pandas is unable to convert the NaN values to integers. We can solve this problem by replacing the NaN values with a constant value. The `fillna` method replaces a Series' null values with the argument we pass in. The next example provides a fill value of 0. Note that your choice of value can distort the data; 0 is passed solely for the sake of example.

We know that the original Salary column has a missing value in its last row. Let's take a look at the last row after we invoke the `fillna` method:

```
In [11] employees["Salary"].fillna(0).tail()

Out [11] 996      42392.0
         997      96914.0
         998      60500.0
         999     129949.0
        1000       0.0
Name: Salary, dtype: float64
```

Excellent. Now that the Salary column has no missing values, we can convert its values to integers with the `astype` method:

```
In [12] employees["Salary"].fillna(0).astype(int).tail()

Out [12] 996      42392
         997      96914
         998      60500
         999     129949
        1000       0
Name: Salary, dtype: int64
```

Next, we can overwrite the existing Salary Series in `employees`:

```
In [13] employees["Salary"] = employees["Salary"].fillna(0).astype(int)
```

We can make one additional optimization. Pandas includes a special data type called a *category*, which is ideal for a column consisting of a small number of unique values relative to its total size. Some everyday examples of data points with a limited number of values include gender, weekdays, blood types, planets, and income groups. Behind the scenes, pandas stores only one copy of each categorical value rather than storing duplicates across rows.

The `nunique` method can reveal the number of unique values in each DataFrame column. Note that it excludes missing values (NaN) from the count by default:

```
In [14] employees.nunique()

Out [14] First Name    200
          Gender        2
          Start Date   971
          Salary       995
          Mgmt         2
          Team        10
          dtype: int64
```

The Gender and Team columns stand out as good candidates to store categorical values. In 1,001 rows of data, Gender has only two unique values, and Team has only ten unique values.

Let's use the `astype` method again. First, we'll convert the Gender column's values to categories by passing an argument of "category" to the method:

```
In [15] employees["Gender"].astype("category")

Out [15] 0      Male
          1      Male
          2    Female
          3      NaN
          4      Male
          ...
          996     Male
          997     Male
          998     Male
          999     Male
          1000    NaN
Name: Gender, Length: 1001, dtype: category
Categories (2, object): [Female, Male]
```

Pandas has identified two unique categories: "Female" and "Male". We're good to overwrite our existing Gender column:

```
In [16] employees["Gender"] = employees["Gender"].astype("category")
```

Let's check in on the memory use by invoking the `info` method. Memory use has dropped significantly once again because pandas has to keep track of only two values instead of 1,001:

```
In [17] employees.info()

Out [17]

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1001 entries, 0 to 1000
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype  
---  --  
 0   First Name  933 non-null   object 
 1   Gender       854 non-null   category
 2   Start Date  999 non-null   datetime64[ns]
```

```

3   Salary      1001 non-null    int64
4   Mgmt       1001 non-null     bool
5   Team        957 non-null    object
dtypes: bool(1), category(1), datetime64[ns](1), int64(1), object(2)
memory usage: 33.5+ KB

```

Let's repeat the same process for the Team column, which has only ten unique values:

```

In [18] employees["Team"] = employees["Team"].astype("category")

In [19] employees.info()

Out [19]

```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1001 entries, 0 to 1000
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype  
---  --  
 0   First Name  933 non-null    object 
 1   Gender       854 non-null    category
 2   Start Date  999 non-null    datetime64[ns]
 3   Salary       1001 non-null   int64  
 4   Mgmt        1001 non-null   bool   
 5   Team         957 non-null    category
dtypes: bool(1), category(2)
memory usage: 27.0+ KB

```

With fewer than ten lines of code, we've reduced the DataFrame's memory consumption by more than 40%. Imagine that impact on data sets with millions of rows!

5.2 Filtering by a single condition

Extracting a subset of data is perhaps the most common operation in data analysis. A *subset* is a portion of a larger data set that fits some kind of condition.

Suppose that we want to generate a list of all employees named "Maria". To accomplish this task, we need to filter our employees data set based on the values in the First Name column. The list of employees named Maria is a subset of all employees.

First, a quick reminder of how equality works in Python. The equality operator (`==`) compares the equality of two objects in Python, returning `True` if the objects are equal and `False` if they are unequal. (See appendix B for a detailed explanation.) Here's a simple example:

```

In [20] "Maria" == "Maria"
Out [20] True

In [21] "Maria" == "Taylor"
Out [21] False

```

To compare every Series entry with a constant value, we place the Series on one side of the equality operator and the value on the other:

```
Series == value
```

One might think that this syntax would lead to an error, but pandas is smart enough to recognize that we want to compare the equality of each Series value with the specified string, not with the Series itself. We explored similar ideas in chapter 2 when we paired a Series with mathematical operators such as the addition sign.

When we combine a Series with an equality operator, pandas returns a Series of Booleans. The next example compares each First Name column value with "Maria". A True value indicates that the string "Maria" does occur at that index, and a False value indicates that it does not. The following output communicates that index 2 stores the value "Maria":

```
In [22] employees["First Name"] == "Maria"

Out [22] 0      False
         1      False
         2      True
         3      False
         4      False
         ...
        996     False
        997     False
        998     False
        999     False
       1000     False
Name: First Name, Length: 1001, dtype: bool
```

If we could extract only the rows with a True value above from our employees DataFrame, we would have all the "Maria" records in the data set. Luckily, pandas offers a convenient syntax for extracting rows by using a Boolean Series. To filter rows, we provide the Boolean Series between square brackets following the DataFrame:

```
In [23] employees[employees["First Name"] == "Maria"]

Out [23]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|-----|------------|--------|------------|--------|-------|--------------|
| 2 | Maria | Female | NaT | 130590 | False | Finance |
| 198 | Maria | Female | 1990-12-27 | 36067 | True | Product |
| 815 | Maria | NaN | 1986-01-18 | 106562 | False | HR |
| 844 | Maria | NaN | 1985-06-19 | 148857 | False | Legal |
| 936 | Maria | Female | 2003-03-14 | 96250 | False | Business Dev |
| 984 | Maria | Female | 2011-10-15 | 43455 | False | Engineering |

Great success! We've used our Boolean Series to filter rows with a value of "Maria" in the First Name column.

If the use of multiple square brackets is confusing, you can assign the Boolean Series to a descriptive variable and then pass the variable into the square brackets instead. The following code yields the same subset of rows as the preceding code:

```
In [24] marias = employees["First Name"] == "Maria"
employees[marias]
```

```
Out [24]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|-----|-------------------|---------------|-------------------|---------------|-------------|--------------|
| 2 | Maria | Female | NaT | 130590 | False | Finance |
| 198 | Maria | Female | 1990-12-27 | 36067 | True | Product |
| 815 | Maria | NaN | 1986-01-18 | 106562 | False | HR |
| 844 | Maria | NaN | 1985-06-19 | 148857 | False | Legal |
| 936 | Maria | Female | 2003-03-14 | 96250 | False | Business Dev |
| 984 | Maria | Female | 2011-10-15 | 43455 | False | Engineering |

The most common mistake beginners make when comparing the equality of values is using one equal sign instead of two. Remember that a single equal sign assigns an object to a variable, and two equal signs check for equality between objects. If we accidentally used a single equal sign in this example, we would overwrite all the First Name column's values with the string "Maria". No good.

Let's try another example. What if we want to extract a subset of employees who are not on the Finance team? The protocol remains the same, but with a slight twist. We need to generate a Boolean Series that checks which of the Team column's values are not equal to "Finance". Then we can use the Boolean Series to filter employees. Python's inequality operator returns True if two values are not equal and False if they are equal:

```
In [25] "Finance" != "Engineering"
```

```
Out [25] True
```

The Series object plays friendly with the inequality operator as well. The next example compares the values in the Team column with the string "Finance". True denotes that the Team value for a given index is not "Finance", and False indicates the Team value is "Finance":

```
In [26] employees["Team"] != "Finance"
```

```
Out [26] 0      True
        1      True
        2     False
        3     False
        4      True
        ...
       996    False
       997    True
       998    True
       999    True
      1000   True
Name: Team, Length: 1001, dtype: bool
```

Now that we have our Boolean Series, we can pass it inside square brackets to extract the DataFrame rows with a value of True. In the following output, we see that pandas has excluded the rows at indexes 2 and 3 because the Team value there is "Finance":

```
In [27] employees[employees["Team"] != "Finance"]
```

```
Out [27]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|------|------------|--------|------------|--------|-------|--------------|
| 0 | Douglas | Male | 1993-08-06 | 0 | True | Marketing |
| 1 | Thomas | Male | 1996-03-31 | 61933 | True | NaN |
| 4 | Larry | Male | 1998-01-24 | 101004 | True | IT |
| 5 | Dennis | Male | 1987-04-18 | 115163 | False | Legal |
| 6 | Ruby | Female | 1987-08-17 | 65476 | True | Product |
| ... | ... | ... | ... | ... | ... | ... |
| 995 | Henry | NaN | 2014-11-23 | 132483 | False | Distribution |
| 997 | Russell | Male | 2013-05-20 | 96914 | False | Product |
| 998 | Larry | Male | 2013-04-20 | 60500 | False | Business Dev |
| 999 | Albert | Male | 2012-05-15 | 129949 | True | Sales |
| 1000 | NaN | NaN | NaT | 0 | True | NaN |

899 rows × 6 columns

Note that the results include rows with missing values. We can see an example at index 1000. In this scenario, pandas considers a NaN to be unequal to the string "Finance".

What if we want to retrieve all the managers in the company? Managers have a value of True in the Mgmt column. We could execute `employees["Mgmt"] == True`, but we don't need to because Mgmt is already a Series of Booleans. The True values and False values already indicate whether pandas should keep or discard a row. Therefore, we can pass the Mgmt column by itself inside the square brackets:

```
In [28] employees[employees["Mgmt"]].head()
```

```
Out [28]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|---|------------|--------|------------|--------|------|-----------|
| 0 | Douglas | Male | 1993-08-06 | 0 | True | Marketing |
| 1 | Thomas | Male | 1996-03-31 | 61933 | True | NaN |
| 3 | Jerry | NaN | 2005-03-04 | 138705 | True | Finance |
| 4 | Larry | Male | 1998-01-24 | 101004 | True | IT |
| 6 | Ruby | Female | 1987-08-17 | 65476 | True | Product |

We can also use arithmetic operands to filter columns based on mathematical conditions. The next example generates a Boolean Series for Salary values greater than \$100,000 (see chapter 2 for more on this syntax):

```
In [29] high_earners = employees["Salary"] > 100000
high_earners.head()
```

```
Out [29] 0    False
        1    False
        2    True
        3    True
        4    True
Name: Salary, dtype: bool
```

Let's see which employees earn a salary above \$100,000:

```
In [30] employees[high_earners].head()
```

```
Out [30]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|---|------------|--------|------------|--------|-------|--------------|
| 2 | Maria | Female | NaT | 130590 | False | Finance |
| 3 | Jerry | NAN | 2005-03-04 | 138705 | True | Finance |
| 4 | Larry | Male | 1998-01-24 | 101004 | True | IT |
| 5 | Dennis | Male | 1987-04-18 | 115163 | False | Legal |
| 9 | Frances | Female | 2002-08-08 | 139852 | True | Business Dev |

Try practicing the syntax on some of the other columns in `employees`. As long as you provide a Boolean Series, pandas will be able to filter the DataFrame.

5.3 Filtering by multiple conditions

We can filter a DataFrame with multiple conditions by creating two independent Boolean Series and then declaring the logical criterion that pandas should apply between them.

5.3.1 The AND condition

Suppose that we want to find all female employees who work on the business development team. Now pandas must look for two conditions to select a row: a value of "Female" in the Gender column and a value of "Business Dev" in the Team column. The two criteria are independent, but both must be met. Here's a quick reminder of how AND logic works with two conditions:

| Condition 1 | Condition 2 | Evaluation |
|-------------|-------------|------------|
| True | True | True |
| True | False | False |
| False | True | False |
| False | False | False |

Let's construct one Boolean Series at a time. We can begin by isolating the "Female" values in the Gender column:

```
In [31] is_female = employees["Gender"] == "Female"
```

Next, we'll target all employees who work on the "Business Dev" team:

```
In [32] in_biz_dev = employees["Team"] == "Business Dev"
```

Finally, we need to calculate the intersection of the two Series, the rows in which both the `is_female` and `in_biz_dev` Series have True values. Pass both Series into the square brackets, and place an ampersand symbol (&) between them. The

ampersand declares an AND logical criterion. The `is_female` Series must have True and the `in_biz_dev` Series must have True:

```
In [33] employees[is_female & in_biz_dev].head()
```

```
Out [33]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|----|------------|--------|------------|--------|-------|--------------|
| 9 | Frances | Female | 2002-08-08 | 139852 | True | Business Dev |
| 33 | Jean | Female | 1993-12-18 | 119082 | False | Business Dev |
| 36 | Rachel | Female | 2009-02-16 | 142032 | False | Business Dev |
| 38 | Stephanie | Female | 1986-09-13 | 36844 | True | Business Dev |
| 61 | Denise | Female | 2001-11-06 | 106862 | False | Business Dev |

We can include any amount of Series within the square brackets as long as we separate every subsequent two with a & symbol. The next example adds a third criterion to identify the female managers on the business development team:

```
In [34] is_manager = employees["Mgmt"]
       employees[is_female & in_biz_dev & is_manager].head()
```

```
Out [34]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|-----|------------|--------|------------|--------|------|--------------|
| 9 | Frances | Female | 2002-08-08 | 139852 | True | Business Dev |
| 38 | Stephanie | Female | 1986-09-13 | 36844 | True | Business Dev |
| 66 | Nancy | Female | 2012-12-15 | 125250 | True | Business Dev |
| 92 | Linda | Female | 2000-05-25 | 119009 | True | Business Dev |
| 111 | Bonnie | Female | 1999-12-17 | 42153 | True | Business Dev |

In summary, the & symbol selects rows that fit all conditions. Declare two or more Boolean Series and then use the ampersand to weave them together.

5.3.2 The OR condition

We can also extract rows if they fit one of several conditions. Not all conditions have to be true, but at least one does. Here's a quick reminder of how OR logic works with two conditions:

| Condition 1 | Condition 2 | Evaluation |
|-------------|-------------|------------|
| True | True | True |
| True | False | True |
| False | True | True |
| False | False | False |

Suppose that we want to identify all employees with a Salary below \$40,000 or a Start Date after January 1, 2015. We can use mathematical operators such as < and > to arrive at two separate Boolean Series for these conditions:

```
In [35] earning_below_40k = employees["Salary"] < 40000
       started_after_2015 = employees["Start Date"] > "2015-01-01"
```

We use a pipe symbol (|) between Boolean Series to declare OR criteria. The next example selects the rows in which either of the Boolean Series holds a True value:

```
In [36] employees[earning_below_40k | started_after_2015].tail()
Out [36]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|------|------------|--------|------------|--------|-------|-------------|
| 958 | Gloria | Female | 1987-10-24 | 39833 | False | Engineering |
| 964 | Bruce | Male | 1980-05-07 | 35802 | True | Sales |
| 967 | Thomas | Male | 2016-03-12 | 105681 | False | Engineering |
| 989 | Justin | NaN | 1991-02-10 | 38344 | False | Legal |
| 1000 | NaN | NaN | NaT | 0 | True | NaN |

The rows at index positions 958, 964, 989, and 1000 fit the Salary condition, and the row at index 967 fits the Start Date condition. Pandas will also include rows that fit both conditions.

5.3.3 Inversion with ~

The tilde symbol (~) inverts the values in a Boolean Series. All True values become False, and all False values become True. Here's a simple example with a small Series:

```
In [37] my_series = pd.Series([True, False, True])
my_series

Out [37] 0      True
         1      False
         2      True
        dtype: bool

In [38] ~my_series

Out [38] 0      False
         1      True
         2      False
        dtype: bool
```

Inversion is helpful when we'd like to reverse a condition. Let's say we want to identify employees with a Salary of less than \$100,000. We could use two approaches, the first of which is to write `employees["Salary"] < 100000`:

```
In [39] employees[employees["Salary"] < 100000].head()
Out [39]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|---|------------|--------|------------|--------|------|-------------|
| 0 | Douglas | Male | 1993-08-06 | 0 | True | Marketing |
| 1 | Thomas | Male | 1996-03-31 | 61933 | True | NaN |
| 6 | Ruby | Female | 1987-08-17 | 65476 | True | Product |
| 7 | NaN | Female | 2015-07-20 | 45906 | True | Finance |
| 8 | Angela | Female | 2005-11-22 | 95570 | True | Engineering |

Alternatively, we could invert the results set of employees earning more than or equal to \$100,000. The resulting DataFrames will be identical. In the next example, we

wrap our greater-than operation inside a parenthesis. The syntax ensures that pandas generates the Boolean Series before inverting its values. In general, you should use parentheses whenever the order of evaluation may be unclear to pandas:

```
In [40] employees[~(employees["Salary"] >= 100000)].head()
Out [40]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|---|------------|--------|------------|--------|------|-------------|
| 0 | Douglas | Male | 1993-08-06 | 0 | True | Marketing |
| 1 | Thomas | Male | 1996-03-31 | 61933 | True | NaN |
| 6 | Ruby | Female | 1987-08-17 | 65476 | True | Product |
| 7 | NaN | Female | 2015-07-20 | 45906 | True | Finance |
| 8 | Angela | Female | 2005-11-22 | 95570 | True | Engineering |

TIP For complex extractions like this one, consider assigning the Boolean Series to a descriptive variable.

5.3.4 Methods for Booleans

Pandas provides an alternative syntax for analysts who prefer methods over operators. The following table displays the method alternatives for equality, inequality, and other arithmetic operations:

| Operation | Arithmetic syntax | Method syntax |
|--------------------------|----------------------------------|-----------------------------------|
| Equality | employees["Team"] == "Marketing" | employees["Team"].eq("Marketing") |
| Inequality | employees["Team"] != "Marketing" | employees["Team"].ne("Marketing") |
| Less than | employees["Salary"] < 100000 | employees["Salary"].lt(100000) |
| Less than or equal to | employees["Salary"] <= 100000 | employees["Salary"].le(100000) |
| Greater than | employees["Salary"] > 100000 | employees["Salary"].gt(100000) |
| Greater than or equal to | employees["Salary"] >= 100000 | employees["Salary"].ge(100000) |

The same rules apply regarding the use of & and | symbols for AND/OR logic.

5.4 Filtering by condition

Some filtering operations are more complex than simple equality or inequality checks. Luckily, pandas ships with many helper methods that generate Boolean Series for these types of extractions.

5.4.1 The `isin` method

What if we want to isolate the employees who belong to either the Sales, Legal, or Marketing team? We could provide three separate Boolean Series inside the square brackets and add the | symbol to declare OR criteria:

```
In [41]: sales = employees["Team"] == "Sales"
         legal = employees["Team"] == "Legal"
         mktg = employees["Team"] == "Marketing"
         employees[sales | legal | mktg].head()
```

Out [41]

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|----|------------|--------|------------|--------|-------|-----------|
| 0 | Douglas | Male | 1993-08-06 | 0 | True | Marketing |
| 5 | Dennis | Male | 1987-04-18 | 115163 | False | Legal |
| 11 | Julie | Female | 1997-10-26 | 102508 | True | Legal |
| 13 | Gary | Male | 2008-01-27 | 109831 | False | Sales |
| 20 | Lois | NaN | 1995-04-22 | 64714 | True | Legal |

Although this solution works, it isn't scalable. What if our next report asked for employees from 15 teams instead of three? Declaring a Series for each condition is laborious.

A better solution is the `isin` method, which accepts an iterable of elements (list, tuple, Series, and so on) and returns a Boolean Series. `True` denotes that pandas found the row's value among the iterable's values, and `False` denotes that it did not. When we have the Series, we can use it to filter the DataFrame in the usual manner. The next example achieves the same result set:

```
In [42]: all_star_teams = ["Sales", "Legal", "Marketing"]
         on_all_star_teams = employees["Team"].isin(all_star_teams)
         employees[on_all_star_teams].head()
```

Out [42]

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|----|------------|--------|------------|--------|-------|-----------|
| 0 | Douglas | Male | 1993-08-06 | 0 | True | Marketing |
| 5 | Dennis | Male | 1987-04-18 | 115163 | False | Legal |
| 11 | Julie | Female | 1997-10-26 | 102508 | True | Legal |
| 13 | Gary | Male | 2008-01-27 | 109831 | False | Sales |
| 20 | Lois | NaN | 1995-04-22 | 64714 | True | Legal |

An optimal situation for using the `isin` method is when we do not know the comparison collection in advance, such as when it is generated dynamically.

5.4.2 The between method

When working with numbers or dates, we often want to extract values that fall within a range. Suppose that we want to identify all employees with a salary between \$80,000 and \$90,000. We could create two Boolean Series, one to declare the lower bound and one to declare the upper bound. Then we could use the `&` operator to mandate that both conditions are `True`:

```
In [43]: higher_than_80 = employees["Salary"] >= 80000
         lower_than_90 = employees["Salary"] < 90000
         employees[higher_than_80 & lower_than_90].head()
```

Out [43]

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|----|------------|--------|------------|--------|-------|-------------|
| 19 | Donna | Female | 2010-07-22 | 81014 | False | Product |
| 31 | Joyce | Nan | 2005-02-20 | 88657 | False | Product |
| 35 | Theresa | Female | 2006-10-10 | 85182 | False | Sales |
| 45 | Roger | Male | 1980-04-17 | 88010 | True | Sales |
| 54 | Sara | Female | 2007-08-15 | 83677 | False | Engineering |

A slightly cleaner solution is to use a method called `between`, which accepts a lower bound and an upper bound; it returns a Boolean Series where `True` denotes that a row's value falls between the specified interval. Note that the first argument, the lower bound, is inclusive, and the second argument, the upper bound, is exclusive. The following code returns the same DataFrame as the preceding code, filtering for salaries between \$80,000 and \$90,000:

```
In [44]: between_80k_and_90k = employees["Salary"].between(80000, 90000)
          employees[between_80k_and_90k].head()
```

Out [44]

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|----|------------|--------|------------|--------|-------|-------------|
| 19 | Donna | Female | 2010-07-22 | 81014 | False | Product |
| 31 | Joyce | Nan | 2005-02-20 | 88657 | False | Product |
| 35 | Theresa | Female | 2006-10-10 | 85182 | False | Sales |
| 45 | Roger | Male | 1980-04-17 | 88010 | True | Sales |
| 54 | Sara | Female | 2007-08-15 | 83677 | False | Engineering |

The `between` method also works on columns of other data types. To filter datetimes, we can pass strings for the start and end dates of our time range. The keyword parameters for the first and second arguments of the method are `left` and `right`. Here, we find all employees who started with the company in the 1980s:

```
In [45]: eighties_folk = employees["Start Date"].between(
              left = "1980-01-01",
              right = "1990-01-01"
            )
          employees[eighties_folk].head()
```

Out [45]

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|----|------------|--------|------------|--------|-------|---------|
| 5 | Dennis | Male | 1987-04-18 | 115163 | False | Legal |
| 6 | Ruby | Female | 1987-08-17 | 65476 | True | Product |
| 10 | Louise | Female | 1980-08-12 | 63241 | True | Nan |
| 12 | Brandon | Male | 1980-12-01 | 112807 | True | HR |
| 17 | Shawn | Male | 1986-12-07 | 111737 | False | Product |

We can also apply the `between` method to string columns. Let's extract all employees whose first names starts with the letter "R". We'll start with a capital "R" as our inclusive lower bound and go up to the noninclusive upper bound of "S":

```
In [46] name_starts_with_r = employees["First Name"].between("R", "S")
employees[name_starts_with_r].head()
```

```
Out [46]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|----|------------|--------|------------|--------|-------|--------------|
| 6 | Ruby | Female | 1987-08-17 | 65476 | True | Product |
| 36 | Rachel | Female | 2009-02-16 | 142032 | False | Business Dev |
| 45 | Roger | Male | 1980-04-17 | 88010 | True | Sales |
| 67 | Rachel | Female | 1999-08-16 | 51178 | True | Finance |
| 78 | Robin | Female | 1983-06-04 | 114797 | True | Sales |

As always, be mindful of case sensitivity when working with characters and strings.

5.4.3 The `isnull` and `notnull` methods

The employees data set includes plenty of missing values. We can see a few missing values in our first five rows:

```
In [47] employees.head()
```

```
Out [47]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|---|------------|--------|------------|--------|-------|-----------|
| 0 | Douglas | Male | 1993-08-06 | 0 | True | Marketing |
| 1 | Thomas | Male | 1996-03-31 | 61933 | True | NaN |
| 2 | Maria | Female | Nat | 130590 | False | Finance |
| 3 | Jerry | | Nan | 138705 | True | Finance |
| 4 | Larry | Male | 1998-01-24 | 101004 | True | IT |

Pandas marks missing text values and missing numeric values with a `NaN` (not a number) designation, and it marks missing datetime values with a `Nat` (not a time) designation. We can see an example in the Start Date column at index position 2.

We can use several pandas methods to isolate rows with either null or present values in a given column. The `isnull` method returns a Boolean Series in which `True` denotes that a row's value is missing:

```
In [48] employees["Team"].isnull().head()
```

```
Out [48] 0    False
        1    True
        2    False
        3    False
        4    False
Name: Team, dtype: bool
```

Pandas considers the `Nat` and `None` values to be null as well. The next example invokes the `isnull` method on the Start Date column:

```
In [49] employees["Start Date"].isnull().head()
```

```
Out [49] 0    False
        1    False
        2    True
        3    False
        4    False
Name: Start Date, dtype: bool
```

The `notnull` method returns the inverse Series, one in which `True` indicates that a row's value is present. The following output communicates that indices 0, 2, 3, and 4 do not have missing values:

```
In [50] employees["Team"].notnull().head()

Out [50] 0      True
         1     False
         2      True
         3      True
         4      True
Name: Team, dtype: bool
```

We can produce the same result set by inverting the Series returned by the `isnull` method. As a reminder, we use the tilde symbol (`~`) to invert a Boolean Series:

```
In [51] (~employees["Team"].isnull()).head()

Out [51] 0      True
         1     False
         2      True
         3      True
         4      True
Name: Team, dtype: bool
```

Either approach works, but `notnull` is a bit more descriptive and thus is recommended.

As always, we can use these Boolean Series to extract specific DataFrame rows. Here, we extract all employees with a missing Team value:

```
In [52] no_team = employees["Team"].isnull()
        employees[no_team].head()

Out [52]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|----|-------------------|---------------|-------------------|---------------|-------------|-------------|
| 1 | Thomas | Male | 1996-03-31 | 61933 | True | NaN |
| 10 | Louise | Female | 1980-08-12 | 63241 | True | NaN |
| 23 | NaN | Male | 2012-06-14 | 125792 | True | NaN |
| 32 | NaN | Male | 1998-08-21 | 122340 | True | NaN |
| 91 | James | Nan | 2005-01-26 | 128771 | False | NaN |

The next example pulls out employees with a present First Name value:

```
In [53] has_name = employees["First Name"].notnull()
        employees[has_name].tail()

Out [53]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|-----|-------------------|---------------|-------------------|---------------|-------------|--------------|
| 995 | Henry | NaN | 2014-11-23 | 132483 | False | Distribution |
| 996 | Phillip | Male | 1984-01-31 | 42392 | False | Finance |
| 997 | Russell | Male | 2013-05-20 | 96914 | False | Product |
| 998 | Larry | Male | 2013-04-20 | 60500 | False | Business Dev |
| 999 | Albert | Male | 2012-05-15 | 129949 | True | Sales |

The `isnull` and `notnull` methods are the best way to quickly filter for present and missing values in one or more rows.

5.4.4 Dealing with null values

While we're on the topic of missing values, let's discuss some options for dealing with them. In section 5.2, we learned how to use the `fillna` method to replace NaNs with a constant value. We could also remove them.

Let's kick off this section by bringing our data set back to its original shape. We'll reimport the CSV by using the `read_csv` function:

```
In [54] employees = pd.read_csv(
        "employees.csv", parse_dates = ["Start Date"]
    )
```

Here's a reminder of what it looks like:

```
In [55] employees
```

```
Out [55]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|------|-------------------|---------------|-------------------|---------------|-------------|--------------|
| 0 | Douglas | Male | 1993-08-06 | NaN | True | Marketing |
| 1 | Thomas | Male | 1996-03-31 | 61933.0 | True | NaN |
| 2 | Maria | Female | NaT | 130590.0 | False | Finance |
| 3 | Jerry | Nan | 2005-03-04 | 138705.0 | True | Finance |
| 4 | Larry | Male | 1998-01-24 | 101004.0 | True | IT |
| ... | ... | ... | ... | ... | ... | ... |
| 996 | Phillip | Male | 1984-01-31 | 42392.0 | False | Finance |
| 997 | Russell | Male | 2013-05-20 | 96914.0 | False | Product |
| 998 | Larry | Male | 2013-04-20 | 60500.0 | False | Business Dev |
| 999 | Albert | Male | 2012-05-15 | 129949.0 | True | Sales |
| 1000 | NaN | NaN | NaT | NaN | NaN | NaN |

1001 rows × 6 columns

The `dropna` method removes DataFrame rows that hold any NaN values. It doesn't matter how many values a row is missing; the method excludes the row if a single NaN is present. The employees DataFrame has a missing value at index 0 of the Salary column, index 1 of the Team column, index 2 of the Start Date column, and index 3 of the Gender column. Notice that pandas excludes all these rows in the following output:

```
In [56] employees.dropna()
```

```
Out [56]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|-----|-------------------|---------------|-------------------|---------------|-------------|--------------|
| 4 | Larry | Male | 1998-01-24 | 101004.0 | True | IT |
| 5 | Dennis | Male | 1987-04-18 | 115163.0 | False | Legal |
| 6 | Ruby | Female | 1987-08-17 | 65476.0 | True | Product |
| 8 | Angela | Female | 2005-11-22 | 95570.0 | True | Engineering |
| 9 | Frances | Female | 2002-08-08 | 139852.0 | True | Business Dev |
| ... | ... | ... | ... | ... | ... | ... |

```

994    George    Male 2013-06-21    98874.0    True    Marketing
996    Phillip   Male 1984-01-31    42392.0    False   Finance
997    Russell   Male 2013-05-20    96914.0    False   Product
998    Larry     Male 2013-04-20    60500.0    False  Business Dev
999    Albert    Male 2012-05-15   129949.0    True    Sales

```

761 rows × 6 columns

We can pass the `how` parameter an argument of "all" to remove rows in which all values are missing. Only one row in the data set, the last one, satisfies this condition:

```
In [57] employees.dropna(how = "all").tail()
```

```
Out [57]
```

| | First | Name | Gender | Start Date | Salary | Mgmt | Team |
|-----|---------|------|------------|------------|--------|--------------|------|
| 995 | Henry | NaN | 2014-11-23 | 132483.0 | False | Distribution | |
| 996 | Phillip | Male | 1984-01-31 | 42392.0 | False | Finance | |
| 997 | Russell | Male | 2013-05-20 | 96914.0 | False | Product | |
| 998 | Larry | Male | 2013-04-20 | 60500.0 | False | Business Dev | |
| 999 | Albert | Male | 2012-05-15 | 129949.0 | True | Sales | |

The `how` parameter's default argument is "any". An argument of "any" removes a row if any of its values is absent. Notice that the row at index label 995 has NaN in the Gender column of the preceding output. Compare that output with the following output, in which row 995 is not present; pandas still removes the last row because it has at least one NaN value:

```
In [58] employees.dropna(how = "any").tail()
```

```
Out [58]
```

| | First | Name | Gender | Start Date | Salary | Mgmt | Team |
|-----|---------|------|------------|------------|--------|--------------|------|
| 994 | George | Male | 2013-06-21 | 98874.0 | True | Marketing | |
| 996 | Phillip | Male | 1984-01-31 | 42392.0 | False | Finance | |
| 997 | Russell | Male | 2013-05-20 | 96914.0 | False | Product | |
| 998 | Larry | Male | 2013-04-20 | 60500.0 | False | Business Dev | |
| 999 | Albert | Male | 2012-05-15 | 129949.0 | True | Sales | |

We can use the `subset` parameter to target rows with a missing value in a specific column. The next example removes rows that have a missing value in the Gender column:

```
In [59] employees.dropna(subset = ["Gender"]).tail()
```

```
Out [59]
```

| | First | Name | Gender | Start Date | Salary | Mgmt | Team |
|-----|---------|------|------------|------------|--------|--------------|------|
| 994 | George | Male | 2013-06-21 | 98874.0 | True | Marketing | |
| 996 | Phillip | Male | 1984-01-31 | 42392.0 | False | Finance | |
| 997 | Russell | Male | 2013-05-20 | 96914.0 | False | Product | |
| 998 | Larry | Male | 2013-04-20 | 60500.0 | False | Business Dev | |
| 999 | Albert | Male | 2012-05-15 | 129949.0 | True | Sales | |

We can also pass the `subset` parameter a list of columns. Pandas will remove a row if it has a missing value in any of the specified columns. The next example removes rows with missing values in the Start Date column, the Salary column, or both:

```
In [60] employees.dropna(subset = ["Start Date", "Salary"]).head()
Out [60]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|---|------------|--------|------------|----------|-------|---------|
| 1 | Thomas | Male | 1996-03-31 | 61933.0 | True | NaN |
| 3 | Jerry | Nan | 2005-03-04 | 138705.0 | True | Finance |
| 4 | Larry | Male | 1998-01-24 | 101004.0 | True | IT |
| 5 | Dennis | Male | 1987-04-18 | 115163.0 | False | Legal |
| 6 | Ruby | Female | 1987-08-17 | 65476.0 | True | Product |

The `thresh` parameter specifies a minimum threshold of non-null values that a row must have for pandas to keep it. The next example filters `employees` for rows with at least four present values:

```
In [61] employees.dropna(how = "any", thresh = 4).head()
Out [61]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|---|------------|--------|------------|----------|-------|-----------|
| 0 | Douglas | Male | 1993-08-06 | NaN | True | Marketing |
| 1 | Thomas | Male | 1996-03-31 | 61933.0 | True | NaN |
| 2 | Maria | Female | Nat | 130590.0 | False | Finance |
| 3 | Jerry | Nan | 2005-03-04 | 138705.0 | True | Finance |
| 4 | Larry | Male | 1998-01-24 | 101004.0 | True | IT |

The `thresh` parameter is great when a certain number of missing values renders a row useless for analysis.

5.5 Dealing with duplicates

Missing values are a common occurrence in messy data sets, and so are duplicate values. Luckily, pandas includes several methods for identifying and excluding duplicate values.

5.5.1 The `duplicated` method

First up, here's a quick reminder of the first five rows of the Team column. Notice that the value "Finance" appears at index positions 2 and 3:

```
In [62] employees["Team"].head()
Out [62] 0      Marketing
         1        NaN
         2      Finance
         3      Finance
         4        IT
Name: Team, dtype: object
```

The `duplicated` method returns a Boolean Series that identifies duplicates in a column. Pandas returns `True` any time it sees a value that it previously encountered in the Series. Consider the next example. The `duplicated` method marks the first occurrence of "Finance" in the Team column as a nonduplicate with `False`. It marks all subsequent occurrences of "Finance" as duplicates (with `True`). The same logic applies to all other Team values:

```
In [63] employees["Team"].duplicated().head()  
  
Out [63] 0    False  
         1    False  
         2    False  
         3    True  
         4    False  
Name: Team, dtype: bool
```

The `duplicated` method's `keep` parameter informs pandas which duplicate occurrence to keep. Its default argument, "`first`", keeps the first occurrence of each duplicate value. The following code is equivalent to the preceding code:

```
In [64] employees["Team"].duplicated(keep = "first").head()  
  
Out [64] 0    False  
         1    False  
         2    False  
         3    True  
         4    False  
Name: Team, dtype: bool
```

We can also ask pandas to mark the last occurrence of a value in a column as the nonduplicate. Pass a string of "`last`" to the `keep` parameter:

```
In [65] employees["Team"].duplicated(keep = "last")  
  
Out [65] 0      True  
        1      True  
        2      True  
        3      True  
        4      True  
        ...  
       996    False  
       997    False  
       998    False  
       999    False  
      1000    False  
Name: Team, Length: 1001, dtype: bool
```

Let's say we want to extract one employee from each team. One strategy we could use is pulling out the first row for each unique team in the Team column. Our existing `duplicated` method returns a Boolean Series; `True` identifies all duplicate values after the first encounter. If we invert that Series, we'll get a Series in which `True` denotes the first time pandas encounters a value:

```
In [66] (~employees[ "Team" ].duplicated()).head()

Out [66] 0      True
          1      True
          2      True
          3     False
          4      True
Name: Team, dtype: bool
```

Now we can extract one employee per team by passing the Boolean Series inside square brackets. Pandas will include the rows with the first occurrences of a value in the Team column. Note that the library considers NaNs to be a unique value:

```
In [67] first_one_in_team = ~employees[ "Team" ].duplicated()
employees[first_one_in_team]

Out [67]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|----|------------|--------|------------|----------|-------|--------------|
| 0 | Douglas | Male | 1993-08-06 | NaN | True | Marketing |
| 1 | Thomas | Male | 1996-03-31 | 61933.0 | True | NaN |
| 2 | Maria | Female | Nat | 130590.0 | False | Finance |
| 4 | Larry | Male | 1998-01-24 | 101004.0 | True | IT |
| 5 | Dennis | Male | 1987-04-18 | 115163.0 | False | Legal |
| 6 | Ruby | Female | 1987-08-17 | 65476.0 | True | Product |
| 8 | Angela | Female | 2005-11-22 | 95570.0 | True | Engineering |
| 9 | Frances | Female | 2002-08-08 | 139852.0 | True | Business Dev |
| 12 | Brandon | Male | 1980-12-01 | 112807.0 | True | HR |
| 13 | Gary | Male | 2008-01-27 | 109831.0 | False | Sales |
| 40 | Michael | Male | 2008-10-10 | 99283.0 | True | Distribution |

This output tells us that Douglas is the first employee on the Marketing team in the data set, Thomas is the first one with a missing team, Maria is the first one on the Finance team, and so on.

5.5.2 The drop_duplicates method

A DataFrame's `drop_duplicates` method provides a convenient shortcut for accomplishing the operation in section 5.5.1. By default, the method removes rows in which all values are equal to those in a previously encountered row. There are no employees rows in which all six row values are equal, so the method doesn't accomplish much for us with a standard invocation:

```
In [68] employees.drop_duplicates()

Out [68]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|-----|------------|--------|------------|----------|-------|-----------|
| 0 | Douglas | Male | 1993-08-06 | NaN | True | Marketing |
| 1 | Thomas | Male | 1996-03-31 | 61933.0 | True | NaN |
| 2 | Maria | Female | Nat | 130590.0 | False | Finance |
| 3 | Jerry | Nan | 2005-03-04 | 138705.0 | True | Finance |
| 4 | Larry | Male | 1998-01-24 | 101004.0 | True | IT |
| ... | ... | ... | ... | ... | ... | ... |

```

996    Phillip    Male 1984-01-31    42392.0  False      Finance
997    Russell    Male 2013-05-20    96914.0  False      Product
998    Larry      Male 2013-04-20    60500.0  False  Business Dev
999    Albert     Male 2012-05-15   129949.0  True       Sales
1000   NaN        NaN    NaT        NaN      NaN      NaN

```

1001 rows × 6 columns

But we can pass the method a `subset` parameter with a list of columns that pandas should use to determine a row's uniqueness. The next example finds the first occurrence of each unique value in the `Team` column. In other words, pandas keeps a row only if it has the first occurrence of a `Team` value (such as "Marketing"). It excludes all rows with duplicate `Team` values after the first one:

```
In [69] employees.drop_duplicates(subset = ["Team"])
```

```
Out [69]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|----|-------------------|---------------|-------------------|---------------|-------------|--------------|
| 0 | Douglas | Male | 1993-08-06 | NaN | True | Marketing |
| 1 | Thomas | Male | 1996-03-31 | 61933.0 | True | NaN |
| 2 | Maria | Female | NaT | 130590.0 | False | Finance |
| 4 | Larry | Male | 1998-01-24 | 101004.0 | True | IT |
| 5 | Dennis | Male | 1987-04-18 | 115163.0 | False | Legal |
| 6 | Ruby | Female | 1987-08-17 | 65476.0 | True | Product |
| 8 | Angela | Female | 2005-11-22 | 95570.0 | True | Engineering |
| 9 | Frances | Female | 2002-08-08 | 139852.0 | True | Business Dev |
| 12 | Brandon | Male | 1980-12-01 | 112807.0 | True | HR |
| 13 | Gary | Male | 2008-01-27 | 109831.0 | False | Sales |
| 40 | Michael | Male | 2008-10-10 | 99283.0 | True | Distribution |

The `drop_duplicates` method also accepts a `keep` parameter. We can pass it an argument of "last" to keep the rows with each duplicate value's last occurrence. These rows are likely to be closer to the end of the data set. In the following example, Alice is the last employee in the data set on the HR team, Justin is the last employee on the Legal team, and so on:

```
In [70] employees.drop_duplicates(subset = ["Team"], keep = "last")
```

```
Out [70]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|------|-------------------|---------------|-------------------|---------------|-------------|--------------|
| 988 | Alice | Female | 2004-10-05 | 47638.0 | False | HR |
| 989 | Justin | Nan | 1991-02-10 | 38344.0 | False | Legal |
| 990 | Robin | Female | 1987-07-24 | 100765.0 | True | IT |
| 993 | Tina | Female | 1997-05-15 | 56450.0 | True | Engineering |
| 994 | George | Male | 2013-06-21 | 98874.0 | True | Marketing |
| 995 | Henry | Nan | 2014-11-23 | 132483.0 | False | Distribution |
| 996 | Phillip | Male | 1984-01-31 | 42392.0 | False | Finance |
| 997 | Russell | Male | 2013-05-20 | 96914.0 | False | Product |
| 998 | Larry | Male | 2013-04-20 | 60500.0 | False | Business Dev |
| 999 | Albert | Male | 2012-05-15 | 129949.0 | True | Sales |
| 1000 | NaN | NaN | NaT | NaN | NaN | NaN |

One additional option is available for the `keep` parameter. We can pass an argument of `False` to exclude all rows with duplicate values. Pandas will reject a row if there are any other rows with the same value. The next example filters for rows in `employees` with a unique value in the First Name column. In other words, these first names occur only once in the DataFrame:

```
In [71] employees.drop_duplicates(subset = ["First Name"], keep = False)
Out [71]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|-----|-------------------|---------------|-------------------|---------------|-------------|--------------|
| 5 | Dennis | Male | 1987-04-18 | 115163.0 | False | Legal |
| 8 | Angela | Female | 2005-11-22 | 95570.0 | True | Engineering |
| 33 | Jean | Female | 1993-12-18 | 119082.0 | False | Business Dev |
| 190 | Carol | Female | 1996-03-19 | 57783.0 | False | Finance |
| 291 | Tammy | Female | 1984-11-11 | 132839.0 | True | IT |
| 495 | Eugene | Male | 1984-05-24 | 81077.0 | False | Sales |
| 688 | Brian | Male | 2007-04-07 | 93901.0 | True | Legal |
| 832 | Keith | Male | 2003-02-12 | 120672.0 | False | Legal |
| 887 | David | Male | 2009-12-05 | 92242.0 | False | Legal |

Let's say we want to identify duplicates by a combination of values across multiple columns. We may want the first occurrence of each employee with a unique combination of First Name and Gender in the data set, for example. For reference, here's a subset of all employees with a First Name of "Douglas" and a Gender of "Male":

```
In [72] name_is_douglas = employees["First Name"] == "Douglas"
        is_male = employees["Gender"] == "Male"
        employees[name_is_douglas & is_male]
```

```
Out [72]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|-----|-------------------|---------------|-------------------|---------------|-------------|-------------|
| 0 | Douglas | Male | 1993-08-06 | NaN | True | Marketing |
| 217 | Douglas | Male | 1999-09-03 | 83341.0 | True | IT |
| 322 | Douglas | Male | 2002-01-08 | 41428.0 | False | Product |
| 835 | Douglas | Male | 2007-08-04 | 132175.0 | False | Engineering |

We can pass a list of columns to the `drop_duplicates` method's `subset` parameter. Pandas will use the columns to determine the presence of duplicates. The next example uses a combination of values across the Gender and Team columns to identify duplicates:

```
In [73] employees.drop_duplicates(subset = ["Gender", "Team"]).head()
```

```
Out [73]
```

| | First Name | Gender | Start Date | Salary | Mgmt | Team |
|---|-------------------|---------------|-------------------|---------------|-------------|-------------|
| 0 | Douglas | Male | 1993-08-06 | NaN | True | Marketing |
| 1 | Thomas | Male | 1996-03-31 | 61933.0 | True | NaN |
| 2 | Maria | Female | Nat | 130590.0 | False | Finance |
| 3 | Jerry | Nan | 2005-03-04 | 138705.0 | True | Finance |
| 4 | Larry | Male | 1998-01-24 | 101004.0 | True | IT |

Let's walk through the output. The row at index 0 holds the first occurrence of the name "Douglas" and the gender "Male" in the employees data set. Pandas will exclude any other rows with the same two values from the results set. To clarify, the library will still include a row if it has a First Name of "Douglas" and a Gender not equal to "Male". Similarly, it will include rows with Gender of "Male" and a First Name not equal to "Douglas". Pandas uses the combination of values across the two columns to identify the duplicates.

5.6 Coding challenge

Here's your chance to practice the concepts introduced in this chapter.

5.6.1 Problems

The netflix.csv data set is a collection of almost 6,000 titles that were available to watch in November 2019 on the video streaming service Netflix. It includes four columns: the video's title, director, the date Netflix added it, and its type/category. The director and date_added columns contain missing values. We can see examples at index positions 0, 2, and 5836 of the following output:

```
In [74] pd.read_csv("netflix.csv")
Out [74]
```

| | title | director | date_added | type |
|------|-----------------------|----------------|------------|---------|
| 0 | Alias Grace | NaN | 3-Nov-17 | TV Show |
| 1 | A Patch of Fog | Michael Lennox | 15-Apr-17 | Movie |
| 2 | Lunatics | NaN | 19-Apr-19 | TV Show |
| 3 | Uriyadi 2 | Vijay Kumar | 2-Aug-19 | Movie |
| 4 | Shrek the Musical | Jason Moore | 29-Dec-13 | Movie |
| ... | ... | ... | ... | ... |
| 5832 | The Pursuit | John Papola | 7-Aug-19 | Movie |
| 5833 | Hurricane Bianca | Matt Kugelman | 1-Jan-17 | Movie |
| 5834 | Amar's Hands | Khaled Youssef | 26-Apr-19 | Movie |
| 5835 | Bill Nye: Science Guy | Jason Sussberg | 25-Apr-18 | Movie |
| 5836 | Age of Glory | NaN | NaN | TV Show |

5837 rows × 4 columns

Using the skills you learned in this chapter, solve the following challenges:

- 1 Optimize the data set for limited memory use and maximum utility.
- 2 Find all rows with a title of "Limitless".
- 3 Find all rows with a director of "Robert Rodriguez" and a type of "Movie".
- 4 Find all rows with either a date_added of "2019-07-31" or a director of "Robert Altman".
- 5 Find all rows with a director of "Orson Welles", "Aditya Kripalani", or "Sam Raimi".
- 6 Find all rows with a date_added value between May 1, 2019 and June 1, 2019.
- 7 Drop all rows with a NaN value in the director column.
- 8 Identify the days when Netflix added only one movie to its catalog.

5.6.2 Solutions

Let's tackle the questions!

- 1 To optimize the data set for memory and utility, we can first convert the date_added column's values to datetimes. We can force the type coercion during the import with the parse_dates parameter to the read_csv function:

```
In [75] netflix = pd.read_csv("netflix.csv", parse_dates = ["date_added"])
```

It's important to keep benchmarks, so let's take a look at current memory use:

```
In [76] netflix.info()
```

```
Out [76]
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5837 entries, 0 to 5836
Data columns (total 4 columns):
 #   Column      Non-Null Count  Dtype  
--- 
 0   title       5837 non-null    object  
 1   director    3936 non-null    object  
 2   date_added  5195 non-null    datetime64[ns]
 3   type        5837 non-null    object  
dtypes: datetime64[ns] (1), object (3)
memory usage: 182.5+ KB
```

Can we convert any column's values to a different data type? How about categorical values? Let's use the nunique method to count the number of unique values per column:

```
In [77] netflix.nunique()
```

```
Out [77] title      5780
         director   3024
         date_added 1092
         type        2
         dtype: int64
```

The type column is a perfect candidate for categorical values. In a data set of 5,837 rows, it has only two unique values: "Movie" and "TV Show". We can convert its values by using the astype method. Remember to overwrite the original Series:

```
In [78] netflix["type"] = netflix["type"].astype("category")
```

How much has the conversion to categorical data reduced our memory use? A whopping 22%:

```
In [79] netflix.info()
```

```
Out [79]
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5837 entries, 0 to 5836
```

```
Data columns (total 4 columns):
 #   Column      Non-Null Count  Dtype  
--- 
 0   title        5837 non-null    object  
 1   director     3936 non-null    object  
 2   date_added   5195 non-null    datetime64[ns]
 3   type         5837 non-null    category
 dtypes: category(1), datetime64[ns](1), object(2)
 memory usage: 142.8+ KB
```

- 2 We'll need to use the equality operator to compare each title column value with the string "Limitless". Afterward, we can use the Boolean Series to extract rows from netflix for which the evaluation returns True:

```
In [80] netflix[netflix["title"] == "Limitless"]
```

```
Out [80]
```

| | title | director | date_added | type |
|------|--------------|-----------------|-------------------|-------------|
| 1559 | Limitless | Neil Burger | 2019-05-16 | Movie |
| 2564 | Limitless | NaN | 2016-07-01 | TV Show |
| 4579 | Limitless | Vrinda Samartha | 2019-10-01 | Movie |

- 3 To extract movies directed by Robert Rodriguez, we'll need two Boolean Series, one comparing the director column's values with "Robert Rodriguez" and the other comparing the type column's values with "Movie". The & symbol applies AND logic for two Boolean Series:

```
In [81] directed_by_robert_rodriguez = (
    netflix["director"] == "Robert Rodriguez"
)
is_movie = netflix["type"] == "Movie"
netflix[directed_by_robert_rodriguez & is_movie]
```

```
Out [81]
```

| | title | director | date_added | type |
|------|-------------------------------------|------------------|-------------------|-------------|
| 1384 | Spy Kids: All the Time in the ... | Robert Rodriguez | 2019-02-19 | Movie |
| 1416 | Spy Kids 3: Game... | Robert Rodriguez | 2019-04-01 | Movie |
| 1460 | Spy Kids 2: The Island of Lost D... | Robert Rodriguez | 2019-03-08 | Movie |
| 2890 | Sin City | Robert Rodriguez | 2019-10-01 | Movie |
| 3836 | Shorts | Robert Rodriguez | 2019-07-01 | Movie |
| 3883 | Spy Kids | Robert Rodriguez | 2019-04-01 | Movie |

- 4 The next question asks all for all titles with a date_added of "2019-07-31" or a director of "Robert Altman". This problem is similar to the preceding one but requires a | symbol for OR logic:

```
In [82] added_on_july_31 = netflix["date_added"] == "2019-07-31"
directed_by_altman = netflix["director"] == "Robert Altman"
netflix[added_on_july_31 | directed_by_altman]
```

```
Out [82]
```

| | | title | director | date_added | type |
|------|---------------------------------|---------------------------|---------------|------------|---------|
| 611 | | Popeye | Robert Altman | 2019-11-24 | Movie |
| 1028 | | The Red Sea Diving Resort | Gideon Raff | 2019-07-31 | Movie |
| 1092 | | Gosford Park | Robert Altman | 2019-11-01 | Movie |
| 3473 | Bangkok Love Stories: Innocence | | Nan | 2019-07-31 | TV Show |
| 5117 | Ramen Shop | | Eric Khoo | 2019-07-31 | Movie |

- 5 The next challenge asks for entries with a director of "Orson Welles", "Aditya Kripalani", or "Sam Raimi". One option is to create three Boolean Series, one for each of the three directors, and then use the `|` operator. But a more concise and scalable way to generate the Boolean Series is to invoke the `isin` method on the director column and pass in the list of directors:

```
In [83] directors = ["Orson Welles", "Aditya Kripalani", "Sam Raimi"]
target_directors = netflix["director"].isin(directors)
netflix[target_directors]
```

Out [83]

| | | title | director | date_added | type |
|------|----------------------------|--------------|------------------|------------|-------|
| 946 | | The Stranger | Orson Welles | 2018-07-19 | Movie |
| 1870 | | The Gift | Sam Raimi | 2019-11-20 | Movie |
| 3706 | | Spider-Man 3 | Sam Raimi | 2019-11-01 | Movie |
| 4243 | Tikli and Laxmi Bomb | | Aditya Kripalani | 2018-08-01 | Movie |
| 4475 | The Other Side of the Wind | | Orson Welles | 2018-11-02 | Movie |
| 5115 | Tottaa Pataaka Item Maal | | Aditya Kripalani | 2019-06-25 | Movie |

- 6 The most concise way to find all rows with a `date_added` value between May 1, 2019 and June 1, 2019, is to use the `between` method. We can provide the two dates as the lower and upper bounds. This approach eliminates the need for two separate Boolean Series:

```
In [84] may_movies = netflix["date_added"].between(
    "2019-05-01", "2019-06-01"
)
netflix[may_movies].head()
```

Out [84]

| | | title | director | date_added | type |
|-----|---------------------|------------|--------------|------------|---------|
| 29 | | Chopsticks | Sachin Yardi | 2019-05-31 | Movie |
| 60 | Away From Home | | Nan | 2019-05-08 | TV Show |
| 82 | III Smoking Barrels | | Sanjib Dey | 2019-06-01 | Movie |
| 108 | Jailbirds | | Nan | 2019-05-10 | TV Show |
| 124 | Pegasus | | Han Han | 2019-05-31 | Movie |

- 7 The `dropna` method removes DataFrame rows with missing values. We have to include the `subset` parameter to limit the columns in which pandas should look for null values. For this question, we'll target `Nan` values in the `director` column:

```
In [85] netflix.dropna(subset = ["director"]).head()
Out [85]
```

| | title | director | date_added | type |
|---|------------------------------------|----------------|------------|-------|
| 1 | A Patch of Fog | Michael Lennox | 2017-04-15 | Movie |
| 3 | Uriyadi 2 | Vijay Kumar | 2019-08-02 | Movie |
| 4 | Shrek the Musical | Jason Moore | 2013-12-29 | Movie |
| 5 | Schubert In Love | Lars Büchel | 2018-03-01 | Movie |
| 6 | We Have Always Lived in the Castle | Stacie Passon | 2019-09-14 | Movie |

- 8 The final challenge asks to identify the days when Netflix added only one movie to the service. One solution is to recognize that the date_added column holds duplicate date values for titles added on the same day. We can invoke the drop_duplicates method with a subset of date_added and the keep parameter set to False. Pandas will remove any rows with duplicate entries in the date_added column. The resulting DataFrame will have the titles that were the only ones added on their respective dates:

```
In [86] netflix.drop_duplicates(subset = ["date_added"], keep = False)
Out [86]
```

| | title | director | date_added | type |
|------|--------------------------------------|-----------------|------------|-------|
| 4 | Shrek the Musical | Jason Moore | 2013-12-29 | Movie |
| 12 | Without Gorky | Cosima Spender | 2017-05-31 | Movie |
| 30 | Anjelah Johnson: Not Fancy | Jay Karas | 2015-10-02 | Movie |
| 38 | One Last Thing | Tim Rouhana | 2019-08-25 | Movie |
| 70 | Marvel's Iron Man & Hulk: Heroes ... | Leo Riley | 2014-02-16 | Movie |
| ... | ... | ... | ... | ... |
| 5748 | Menorca | John Barnard | 2017-08-27 | Movie |
| 5749 | Green Room | Jeremy Saulnier | 2018-11-12 | Movie |
| 5788 | Chris Brown: Welcome to My Life | Andrew Sandler | 2017-10-07 | Movie |
| 5789 | A Very Murray Christmas | Sofia Coppola | 2015-12-04 | Movie |
| 5812 | Little Singham in London | Prakash Satam | 2019-04-22 | Movie |

391 rows × 4 columns

Congratulations on completing the coding challenge!

Summary

- The astype method converts a Series' values to another data type.
- The category data type is ideal when a Series has a small number of unique values.
- Pandas can extract subsets of data from a DataFrame based on one or more conditions.
- Pass a Boolean Series inside square brackets to extract a subset of a DataFrame.
- Use the equality, inequality, and mathematical operators to compare each Series entry with a constant value.

- The & symbol mandates that multiple conditions be met to extract a row.
- The | symbol mandates that either condition be met to extract a row.
- Helper methods such as `isnull`, `notnull`, `between`, and `duplicated` return Boolean Series that we can use to filter data sets.
- The `fillna` method replaces NaNs with a constant value.
- The `dropna` method removes rows with null values. We can customize its arguments to target missing values in all or some columns.

Part 2

Applied pandas

I

In part 1, we laid the groundwork for our mastery of pandas. Now that we're comfortable working with `Series` and `DataFrames`, we can expand our horizons and learn how to tackle common problems in data analysis. Chapter 6 dives right into working with messy text data, including dealing with whitespace and inconsistent character casing. In chapter 7, we learn how to use the powerful `MultiIndex` to store and extract hierarchical data. Chapters 8 and 9 focus on aggregation: pivoting our `DataFrames`, grouping data into buckets, summarizing data, and more. In chapter 10, we explore how to merge datasets by using a variety of joins. Immediately afterward, we learn the ins and outs of working with another common data type, datetimes, in chapter 11. In chapter 12, we look at importing and exporting data sets to and from pandas. Chapter 13 covers how to adjust the library's configuration settings. Finally, chapter 14 provides a tutorial on creating visualizations from our `DataFrames`.

Along the way, we'll practice pandas concepts on more than 30 datasets that cover everything from baby names to breakfast cereals, from Fortune 1000 companies to Nobel Prize winners. You are welcome to proceed through the chapters linearly or explore whichever topic piques your interest most. Consider each chapter here to be a new specialization to add to your pandas toolbox. Good luck!

Working with text data



This chapter covers

- Removing whitespace from strings
- Uppercasing and lowercasing strings
- Finding and replacing characters in strings
- Slicing a string by character index positions
- Splitting text by a delimiter

Text data can get quite messy. Real-world data sets are riddled with incorrect characters, improper letter casings, whitespace, and more. The process of cleaning data is called *wrangling* or *munging*. Often, the majority of our data analysis is dedicated to munging. We may know the insight we want to derive early on, but the difficulty lies in arranging the data in a suitable shape for the manipulation. Luckily for us, one of the primary motivations behind pandas was easing the difficulty of cleaning up improperly formatted text values. The library is battle-tested and flexible. In this chapter, we'll learn how to use pandas to fix all sorts of imperfections in our text data sets. There's a lot of ground to cover, so let's dive right in.

6.1 Letter casing and whitespace

We'll begin by importing pandas in a new Jupyter Notebook:

```
In [1] import pandas as pd
```

This chapter's first data set, `chicago_food_inspections.csv`, is a listing of more than 150,000 food inspections conducted across the city of Chicago. The CSV includes only two columns: one with an establishment's name and the other with its risk ranking. The four risk levels are Risk 1 (High), Risk 2 (Medium), Risk 3 (Low), and a special All for the worst offenders:

```
In [2] inspections = pd.read_csv("chicago_food_inspections.csv")
inspections
```

```
Out [2]
```

| | Name | Risk |
|-------------------------|------------------------------|-----------------|
| 0 | MARRIOT MARQUIS CHICAGO | Risk 1 (High) |
| 1 | JETS PIZZA | Risk 2 (Medium) |
| 2 | ROOM 1520 | Risk 3 (Low) |
| 3 | MARRIOT MARQUIS CHICAGO | Risk 1 (High) |
| 4 | CHARTWELLS | Risk 1 (High) |
| ... | ... | ... |
| 153805 | WOLCOTT'S | Risk 1 (High) |
| 153806 | DUNKIN DONUTS/BASKIN-ROBBINS | Risk 2 (Medium) |
| 153807 | Cafe 608 | Risk 1 (High) |
| 153808 | mr.daniel's | Risk 1 (High) |
| 153809 | TEMPO CAFE | Risk 1 (High) |
| 153810 rows × 2 columns | | |

NOTE `chicago_food_inspections.csv` is a modified version of a data set available from the city of Chicago (<http://mng.bz/9N60>). There are typos and inconsistencies within the data; we have preserved them so that you can see the data irregularities that appear in the real world. I encourage you to consider how you can optimize this data with the techniques you'll learn in this chapter.

We immediately see an issue in the Name column: inconsistency in letter casing. Most row values are uppercase, some are lowercase ("`mr.daniel's`"), and some are normal case ("`Café 608`").

The preceding output does not show another problem hiding in `inspections`: the Name column's values are surrounded by whitespace. We can spot the extra spacing more easily if we isolate the Name Series with square-bracket syntax. Notice that the ends of the rows do not align:

```
In [3] inspections["Name"].head()
```

```
Out [3] 0      MARRIOT MARQUIS CHICAGO
        1          JETS PIZZA
        2          ROOM 1520
        3      MARRIOT MARQUIS CHICAGO
        4          CHARTWELLS
Name: Name, dtype: object
```

We can use the `values` attribute on the `Series` to get the underlying NumPy `ndarray` storing the values. The whitespace is present at the ends and the beginnings of the values:

```
In [4] inspections["Name"].head().values  
Out [4] array([' MARRIOT MARQUIS CHICAGO ', ' JETS PIZZA ',  
               ' ROOM 1520 ', ' MARRIOT MARQUIS CHICAGO ',  
               ' CHARTWELLS '], dtype=object)
```

Let's focus on the whitespace first. We'll deal with the letter casings a little later.

The `Series` object's `str` attribute exposes a `StringMethods` object, a powerful toolbox of methods for working with strings:

```
In [5] inspections["Name"].str  
Out [5] <pandas.core.strings.StringMethods at 0x122ad8510>
```

Any time we'd like to perform string manipulations, we invoke a method on the `StringMethods` object rather than the `Series` itself. Some methods work like Python's native string methods, whereas other methods are exclusive to pandas. For a comprehensive review of Python's string methods, see appendix B.

We can use the `strip` family of methods to remove whitespace from a string. The `lstrip` (left strip) method removes whitespace from the beginning of a string. Here's a basic example:

```
In [6] dessert = " cheesecake "  
      dessert.lstrip()  
  
Out [6] 'cheesecake '
```

The `rstrip` (right strip) method removes whitespace from the end of a string:

```
In [7] dessert.rstrip()  
  
Out [7] ' cheesecake '
```

The `strip` method removes whitespace from both ends of a string:

```
In [8] dessert.strip()  
  
Out [8] 'cheesecake'
```

These three `strip` methods are available on the `StringMethods` object. Each one returns a new `Series` object with the operation applied to every column value. Let's invoke each of them:

```
In [9] inspections["Name"].str.lstrip().head()  
  
Out [9] 0      MARRIOT MARQUIS CHICAGO  
           1                  JETS PIZZA  
           2                  ROOM 1520  
           3      MARRIOT MARQUIS CHICAGO  
           4                  CHARTWELLS  
Name: Name, dtype: object
```

```
In [10] inspections["Name"].str.rstrip().head()

Out [10] 0      MARRIOT MARQUIS CHICAGO
          1              JETS PIZZA
          2              ROOM 1520
          3      MARRIOT MARQUIS CHICAGO
          4              CHARTWELLS
Name: Name, dtype: object

In [11] inspections["Name"].str.strip().head()

Out [11] 0      MARRIOT MARQUIS CHICAGO
          1              JETS PIZZA
          2              ROOM 1520
          3      MARRIOT MARQUIS CHICAGO
          4              CHARTWELLS
Name: Name, dtype: object
```

Now we can overwrite our existing Series with the new one that has no extra whitespace. On the right side of an equal sign, we'll use the `strip` code to create the new Series. On the left side, we'll use square-bracket syntax to denote the column we'd like to overwrite. Python processes the right side of the equal sign first. In summary, we use the Name column to create a new Series without whitespace and then overwrite the Name column with that new Series:

```
In [12] inspections["Name"] = inspections["Name"].str.strip()
```

This one-line solution is suitable for a small data set, but it may quickly become tedious for one with a large number of columns. How can we quickly apply the same logic to all DataFrame columns? You may recall the `columns` attribute, which exposes the iterable `Index` object that holds the DataFrame's column names:

```
In [13] inspections.columns

Out [13] Index(['Name', 'Risk'], dtype='object')
```

We can use Python's `for` loop to iterate over each column, extract it dynamically from the DataFrame, invoke the `str.strip` method to return a new Series, and overwrite the original column. The logic requires only two lines:

```
In [14] for column in inspections.columns:
            inspections[column] = inspections[column].str.strip()
```

All of Python's character casing methods are available on the `StringMethods` object. The `lower` method, for example, lowers all string characters:

```
In [15] inspections["Name"].str.lower().head()

Out [15] 0      marriot marquis chicago
          1              jets pizza
          2              room 1520
          3      marriot marquis chicago
          4              chartwells
Name: Name, dtype: object
```

The complementary `str.upper` method returns a Series with uppercase strings. The next example invokes the method on a different Series because the Name column is mostly uppercase already:

```
In [16] steaks = pd.Series(["porterhouse", "filet mignon", "ribeye"])
       steaks

Out [16] 0      porterhouse
         1      filet mignon
         2      ribeye
        dtype: object

In [17] steaks.str.upper()

Out [17] 0      PORTERHOUSE
         1      FILET MIGNON
         2      RIBEYE
        dtype: object
```

Suppose that we want to get the establishments' names in a more standardized, readable format. We can use the `str.capitalize` method to capitalize the first letter of each string in the Series:

```
In [18] inspections["Name"].str.capitalize().head()

Out [18] 0      Marriot marquis chicago
         1          Jets pizza
         2          Room 1520
         3      Marriot marquis chicago
         4          Chartwells
        Name: Name, dtype: object
```

That's a step in the right direction, but perhaps the best method available is `str.title`, which capitalizes each word's first letter. Pandas uses spaces to identify where one word ends and the next begins:

```
In [19] inspections["Name"].str.title().head()

Out [19] 0      Marriot Marquis Chicago
         1          Jets Pizza
         2          Room 1520
         3      Marriot Marquis Chicago
         4          Chartwells
        Name: Name, dtype: object
```

The `title` method is a fantastic option for dealing with locations, countries, cities, and people's full names.

6.2 String slicing

Let's turn our focus to the Risk column. Each row's value includes both a numeric and categorical representation of the risk (such as 1 and "High"). Here's a reminder of what the column looks like:

```
In [20] inspections["Risk"].head()

Out [20]

0      Risk 1 (High)
1      Risk 2 (Medium)
2      Risk 3 (Low)
3      Risk 1 (High)
4      Risk 1 (High)
Name: Risk, dtype: object
```

Let's say we want to extract the numeric risk value from each row. This operation may appear simple, given the seemingly consistent format of each row, but we have to tread carefully. There is always room for deception in a data set this large:

```
In [21] len(inspections)

Out [21] 153810
```

Do all rows follow a "Risk Number (Risk Level)" format? We can find out by invoking the `unique` method, which returns a NumPy ndarray consisting of the column's unique values:

```
In [22] inspections["Risk"].unique()

Out [22] array(['Risk 1 (High)', 'Risk 2 (Medium)', 'Risk 3 (Low)', 'All',
       nan], dtype=object)
```

We have to account for two additional values: missing NaNs and the 'All' string. How we deal with these values is ultimately up to the analyst and the business. Are the values significant, or can they be discarded? In this scenario, let's propose a compromise: we'll remove the missing NaN values and replace the "All" values with "Risk 4 (Extreme)". We'll pick this approach to ensure that all Risk values have a consistent format.

We can remove missing values from a Series with the `dropna` method introduced in chapter 5. We'll pass its `subset` parameter a list of the DataFrame columns in which pandas should look for NaNs. The next example removes rows in `inspections` with a NaN value in the Risk column:

```
In [23] inspections = inspections.dropna(subset = ["Risk"])
```

Let's check in on unique values in the Risk column:

```
In [24] inspections["Risk"].unique()

Out [24] array(['Risk 1 (High)', 'Risk 2 (Medium)', 'Risk 3 (Low)', 'All'],
       dtype=object)
```

We can use the DataFrame's helpful `replace` method to replace all occurrences of one value with another. The method's first parameter, `to_replace`, sets the value to search for, and its second parameter, `value`, specifies what to replace each

occurrence of it with. The next example replaces the "All" string values with "Risk 4 (Extreme)":

```
In [25] inspections = inspections.replace(  
        to_replace = "All", value = "Risk 4 (Extreme)"  
    )
```

Now we have a consistent format for all values in the Risk column:

```
In [26] inspections["Risk"].unique()  
  
Out [26] array(['Risk 1 (High)', 'Risk 2 (Medium)', 'Risk 3 (Low)',  
               'Risk 4 (Extreme)'], dtype=object)
```

Next, let's continue with our original goal of extracting each row's risk number.

6.3 String slicing and character replacement

We can use the `slice` method on the `StringMethods` object to extract a substring from a string by index position. The method accepts a starting index and an ending index as arguments. The lower bound (the starting point) is inclusive, whereas the upper bound (the endpoint) is exclusive.

Our risk number starts at index position 5 in each string. The next example pulls the characters from index position 5 up to (but not including) index position 6:

```
In [27] inspections["Risk"].str.slice(5, 6).head()  
  
Out [27] 0      1  
        1      2  
        2      3  
        3      1  
        4      1  
Name: Risk, dtype: object
```

We can also replace the `slice` method with Python's list-slicing syntax (see appendix B). The following code returns the same result as the preceding code:

```
In [28] inspections["Risk"].str[5:6].head()  
  
Out [28] 0      1  
        1      2  
        2      3  
        3      1  
        4      1  
Name: Risk, dtype: object
```

What if we want to extract the categorical ranking ("High", "Medium", "Low", and "All") from each row? This challenge is made difficult by the different lengths of the words; we cannot extract the same number of characters from a starting index position. A few solutions are available. We'll discuss the most resilient option, regular expressions, in section 6.7.

For now, let's attack the problem step by step. We can start by using the `slice` method to extract each row's risk category. If we pass the `slice` method a single value, pandas will use it as the lower bound and extract until the end of the string.

The next example pulls the characters from index position 8 to the end of each string. The character at index position 8 is the first letter in each risk type (the "H" in "High", the "M" in "Medium", the "L" in "Low", and the "E" in "Extreme"):

```
In [29] inspections["Risk"].str.slice(8).head()

Out [29] 0      High)
          1     Medium)
          2      Low)
          3     High)
          4     High)
Name: Risk, dtype: object
```

We can use Python's list-slicing syntax, too. Inside the square brackets, provide a starting index position followed by a single colon. The result is identical:

```
In [30] inspections["Risk"].str[8:].head()

Out [30] 0      High)
          1     Medium)
          2      Low)
          3     High)
          4     High)
Name: Risk, dtype: object
```

We still have to deal with the pesky closing parentheses. Here's a cool solution: pass a negative argument to the `str.slice` method. A negative argument sets the index bound relative to the end of the string: `-1` extracts up to the last character, `-2` extracts up to the second-to-last character, and so on. Let's extract a substring from index position 8 up until the last character in each string:

```
In [31] inspections["Risk"].str.slice(8, -1).head()

Out [31] 0      High
          1     Medium
          2      Low
          3     High
          4     High
Name: Risk, dtype: object
```

We've got it! If you prefer list-slicing syntax, you can pass the `-1` after the colon inside the square brackets:

```
In [32] inspections["Risk"].str[8:-1].head()

Out [32] 0      High
          1     Medium
          2      Low
          3     High
          4     High
Name: Risk, dtype: object
```

Another strategy we can use to remove the closing parentheses is the `str.replace` method. We can replace each closing parentheses with an empty string—a string without characters.

Each `str` method returns a new `Series` object with its own `str` attribute. This aspect allows us to chain multiple string methods in sequence, as long as we reference the `str` attribute in each method invocation. The next example chains the `slice` and `replace` methods:

```
In [33] inspections["Risk"].str.slice(8).str.replace(")", "").head()

Out [33] 0      High
         1    Medium
         2      Low
         3      High
         4      High
Name: Risk, dtype: object
```

By slicing from a middle index position and removing the ending parenthesis, we were able to isolate the Risk level for each row.

6.4 Boolean methods

Section 6.3 introduced methods such as `upper` and `slice` that return a `Series` of strings. Other methods available on the `StringMethods` object return a `Series` of Booleans. These methods can prove to be particularly helpful for filtering a `DataFrame`.

Suppose that we want to isolate all establishments with the word "Pizza" in their names. In vanilla Python, we use the `in` operator to search for a substring with a string:

```
In [34] "Pizza" in "Jets Pizza"

Out [34] True
```

The biggest challenge in string matching is case sensitivity. Python will not find the string "pizza" in "Jets Pizza", for example, because of the mismatch in casing of the "p" character:

```
In [35] "pizza" in "Jets Pizza"

Out [35] False
```

To solve this problem, we need to ensure consistent casing across all column values before we check for the presence of a substring. We can look for a lowercase "pizza" in an all-lowercase `Series` or an uppercase "PIZZA" in an all-uppercase `Series`. Let's go with the former approach.

The `contains` method checks for a substring's inclusion in each `Series` value. The method returns `True` when pandas finds the method's argument within the row's string and `False` when it does not. The next example first lowerscases the Name column with the `lower` method and then searches for "pizza" within each row:

```
In [36] inspections["Name"].str.lower().str.contains("pizza").head()

Out [36] 0    False
         1    True
         2   False
         3   False
         4   False
Name: Name, dtype: bool
```

We have a Boolean Series, which we can use to extract all establishments with "Pizza" in their name:

```
In [37] has_pizza = inspections["Name"].str.lower().str.contains("pizza")
inspections[has_pizza]
```

```
Out [37]
```

| | Name | Risk |
|--------|----------------------------------|-----------------|
| 1 | JETS PIZZA | Risk 2 (Medium) |
| 19 | NANCY'S HOME OF STUFFED PIZZA | Risk 1 (High) |
| 27 | NARY'S GRILL & PIZZA , INC. | Risk 1 (High) |
| 29 | NARYS GRILL & PIZZA | Risk 1 (High) |
| 68 | COLUTAS PIZZA | Risk 1 (High) |
| ... | ... | ... |
| 153756 | ANGELO'S STUFFED PIZZA CORP | Risk 1 (High) |
| 153764 | COCHIAROS PIZZA #2 | Risk 1 (High) |
| 153772 | FERNANDO'S MEXICAN GRILL & PIZZA | Risk 1 (High) |
| 153788 | REGGIO'S PIZZA EXPRESS | Risk 1 (High) |
| 153801 | State Street Pizza Company | Risk 1 (High) |

```
3992 rows × 2 columns
```

Notice that pandas preserves the original letter casing of the values in Name. The inspections DataFrame is never mutated. The lower method returns a new Series, and the contains method we invoke on it returns another new Series, which pandas uses to filter rows from the original DataFrame.

What if we want to be more precise in our targeting, perhaps extracting all establishments beginning with the string "tacos"? Now we care about the position of the substring within each string. The str.startswith method solves the problem, returning True if a string begins with its argument:

```
In [38] inspections["Name"].str.lower().str.startswith("tacos").head()
```

```
Out [38] 0    False
         1    False
         2    False
         3    False
         4    False
Name: Name, dtype: bool
```

```
In [39] starts_with_tacos = (
    inspections["Name"].str.lower().str.startswith("tacos")
)
```

```
inspections[starts_with_tacos]
```

```
Out [39]
```

| | Name | Risk |
|--------|-----------------------|---------------|
| 69 | TACOS NIETOS | Risk 1 (High) |
| 556 | TACOS EL TIO 2 INC. | Risk 1 (High) |
| 675 | TACOS DON GABINO | Risk 1 (High) |
| 958 | TACOS EL TIO 2 INC. | Risk 1 (High) |
| 1036 | TACOS EL TIO 2 INC. | Risk 1 (High) |
| ... | ... | ... |
| 143587 | TACOS DE LUNA | Risk 1 (High) |
| 144026 | TACOS GARCIA | Risk 1 (High) |
| 146174 | Tacos Place's 1 | Risk 1 (High) |
| 147810 | TACOS MARIO'S LIMITED | Risk 1 (High) |
| 151191 | TACOS REYNA | Risk 1 (High) |

105 rows × 2 columns

The complementary `str.endswith` method checks for a substring at the end of each Series string:

```
In [40] ends_with_tacos = (
    inspections["Name"].str.lower().str.endswith("tacos")
)

inspections[ends_with_tacos]
```

```
Out [40]
```

| | Name | Risk |
|--------|-----------------|---------------|
| 382 | LAZO'S TACOS | Risk 1 (High) |
| 569 | LAZO'S TACOS | Risk 1 (High) |
| 2652 | FLYING TACOS | Risk 3 (Low) |
| 3250 | JONY'S TACOS | Risk 1 (High) |
| 3812 | PACO'S TACOS | Risk 1 (High) |
| ... | ... | ... |
| 151121 | REYES TACOS | Risk 1 (High) |
| 151318 | EL MACHO TACOS | Risk 1 (High) |
| 151801 | EL MACHO TACOS | Risk 1 (High) |
| 153087 | RAYMOND'S TACOS | Risk 1 (High) |
| 153504 | MIS TACOS | Risk 1 (High) |

304 rows × 2 columns

Whether you're looking for text at the beginning, middle, or end of a string, the `StringMethods` object has a helper method to assist you.

6.5 Splitting strings

Our next data set is a collection of fictional customers. Each row includes the customer's Name and Address. Let's import the `customers.csv` file with the `read_csv` function and assign the `DataFrame` to a `customers` variable:

```
In [41] customers = pd.read_csv("customers.csv")
customers.head()

Out [41]
```

| | Name | Address |
|---|---------------------|--|
| 0 | Frank Manning | 6461 Quinn Groves, East Matthew, New Hampshire, 166... |
| 1 | Elizabeth Johnson | 1360 Tracey Ports Apt. 419, Kyleport, Vermont, 319... |
| 2 | Donald Stephens | 19120 Fleming Manors, Prestonstad, Montana, 23495 |
| 3 | Michael Vincent III | 441 Olivia Creek, Jimmymouth, Georgia, 82991 |
| 4 | Jasmine Zamora | 4246 Chelsey Ford Apt. 310, Karamouth, Utah, 76... |

We can use the `str.len` method to return the length of each row's string. Row 0's value of "Frank Manning", for example, has a length of 13 characters:

```
In [42] customers["Name"].str.len().head()

Out [42] 0    13
         1    17
         2    15
         3    19
         4    14
Name: Name, dtype: int64
```

Suppose that we want to isolate each customer's first and last names in two separate columns. You may be familiar with Python's `split` method, which separates a string by using a specified delimiter. The method returns a list consisting of all the substrings after the split. The next example splits a phone number into a list of three strings by using a hyphen delimiter:

```
In [43] phone_number = "555-123-4567"
        phone_number.split("-")

Out [43] ['555', '123', '4567']
```

The `str.split` method performs the same operation on each row in a `Series`; its return value is a `Series` of lists. We pass the delimiter to the method's first parameter, `pat` (short for *pattern*). The next example splits the values in `Name` by the presence of a space:

```
In [44] # The two lines below are equivalent
        customers["Name"].str.split(pat = " ").head()
        customers["Name"].str.split(" ").head()

Out [44] 0      [Frank, Manning]
         1      [Elizabeth, Johnson]
         2      [Donald, Stephens]
         3      [Michael, Vincent, III]
         4      [Jasmine, Zamora]
Name: Name, dtype: object
```

Next, let's reinvoke the `str.len` method on this new `Series` of lists to get the length of each list. Pandas reacts dynamically to whatever data type a `Series` is storing:

```
In [45] customers["Name"].str.split(" ").str.len().head()

Out [45] 0    2
         1    2
         2    2
```

```
3      3
4      2
Name: Name, dtype: int64
```

We have a small issue. Due to suffixes such as "MD" and "Jr", some names have more than two words. We can see an example at index position 3: Michael Vincent III, which pandas splits into a list of three elements. To ensure an equal number of elements per list, we can limit the number of splits. If we set a maximum threshold of one split, pandas will split a string at the first space and stop. Then we'll have a `Series` consisting of two-element lists. Each list will hold the customer's first name and anything that follows it.

The next example passes an argument of 1 to the `split` method's `n` parameter, which sets the maximum number of splits. Take a look at how pandas deals with "Michael Vincent III" at index 3:

```
In [46] customers["Name"].str.split(pat = " ", n = 1).head()

Out [46] 0      [Frank, Manning]
         1      [Elizabeth, Johnson]
         2      [Donald, Stephens]
         3      [Michael, Vincent III]
         4      [Jasmine, Zamora]
Name: Name, dtype: object
```

Now all our lists have equal lengths. We can use `str.get` to pull out a value from *each* row's list based on its index position. We can target index 0, for example, to pull out the first element of each list, which is the customer's first name:

```
In [47] customers["Name"].str.split(pat = " ", n = 1).str.get(0).head()

Out [47] 0      Frank
         1      Elizabeth
         2      Donald
         3      Michael
         4      Jasmine
Name: Name, dtype: object
```

To pull the last name from each list, we could pass the `get` method an index position of 1:

```
In [48] customers["Name"].str.split(pat = " ", n = 1).str.get(1).head()

Out [48] 0      Manning
         1      Johnson
         2      Stephens
         3      Vincent III
         4      Zamora
Name: Name, dtype: object
```

The `get` method also supports negative arguments. An argument of -1 extracts the last element from each row's list, regardless of how many elements the list holds. The

following code produces the same result as the preceding code and is a bit more versatile in scenarios in which the lists have different lengths:

```
In [49] customers["Name"].str.split(pat = " ", n = 1).str.get(-1).head()

Out [49] 0      Manning
          1      Johnson
          2      Stephens
          3      Vincent III
          4      Zamora
Name: Name, dtype: object
```

So far, so good. We've used two separate `get` method calls to extract the first and last names in two separate `Series`. Wouldn't it be nice to perform the same logic in a single method call? Luckily, the `str.split` method accepts an `expand` parameter, and when we pass it an argument of `True`, the method returns a new `DataFrame` instead of a `Series` of lists:

```
In [50] customers["Name"].str.split(
          pat = " ", n = 1, expand = True
        ).head()

Out [50]
```

| | 0 | 1 |
|---|-----------|-------------|
| 0 | Frank | Manning |
| 1 | Elizabeth | Johnson |
| 2 | Donald | Stephens |
| 3 | Michael | Vincent III |
| 4 | Jasmine | Zamora |

We've got a new `DataFrame`! Because we did not provide custom names for the columns, pandas defaulted to a numeric index on the column axis.

Be careful in these scenarios. If we do not limit the number of splits with the `n` parameter, pandas will place `None` values in rows that do not have sufficient elements:

```
In [51] customers["Name"].str.split(pat = " ", expand = True).head()

Out [51]
```

| | 0 | 1 | 2 |
|---|-----------|----------|------|
| 0 | Frank | Manning | None |
| 1 | Elizabeth | Johnson | None |
| 2 | Donald | Stephens | None |
| 3 | Michael | Vincent | III |
| 4 | Jasmine | Zamora | None |

Now that we've isolated the customers' names, let's attach the new two-column `DataFrame` to the existing `customers` `DataFrame`. On the right side of an equal sign, we'll use the `split` code to create the `DataFrame`. On the left side of the equal sign, we'll provide a list of column names inside a pair of square brackets. Pandas will append these columns to `customers`. The next example adds two new columns, `First Name`

and Last Name, and populates them with the DataFrame returned by the split method:

```
In [52] customers[["First Name", "Last Name"]] = customers[
        "Name"
    ].str.split(pat = " ", n = 1, expand = True)
```

Let's take a look at the result:

```
In [53] customers
```

```
Out [53]
```

| | Name | Address | First Name | Last Name |
|------|---------------------|-------------------------|------------|-------------|
| 0 | Frank Manning | 6461 Quinn Groves, E... | Frank | Manning |
| 1 | Elizabeth Johnson | 1360 Tracey Ports Ap... | Elizabeth | Johnson |
| 2 | Donald Stephens | 19120 Fleming Manors... | Donald | Stephens |
| 3 | Michael Vincent III | 441 Olivia Creek, Ji... | Michael | Vincent III |
| 4 | Jasmine Zamora | 4246 Chelsey Ford Ap... | Jasmine | Zamora |
| ... | ... | ... | ... | ... |
| 9956 | Dana Browning | 762 Andrew Views Apt... | Dana | Browning |
| 9957 | Amanda Anderson | 44188 Day Crest Apt ... | Amanda | Anderson |
| 9958 | Eric Davis | 73015 Michelle Squar... | Eric | Davis |
| 9959 | Taylor Hernandez | 129 Keith Greens, Ha... | Taylor | Hernandez |
| 9960 | Sherry Nicholson | 355 Griffin Valley, ... | Sherry | Nicholson |

9961 rows × 4 columns

Excellent! Now that we've extracted the customers' names to separate columns, we can delete the original Name column. One way is to use the drop method on our customers DataFrame. We'll pass the column's name to the labels parameter and an argument of "columns" to the axis parameter. We need to include the axis parameter to tell pandas to look for the Name label in the columns instead of the rows:

```
In [54] customers = customers.drop(labels = "Name", axis = "columns")
```

Remember that mutational operations do not produce output in Jupyter Notebook. We must print the DataFrame to see the result:

```
In [55] customers.head()
```

```
Out [55]
```

| | Address | First Name | Last Name |
|---|---|------------|-------------|
| 0 | 6461 Quinn Groves, East Matthew, New Hampshire... | Frank | Manning |
| 1 | 1360 Tracey Ports Apt. 419, Kyleport, Vermont... | Elizabeth | Johnson |
| 2 | 19120 Fleming Manors, Prestonstad, Montana... | Donald | Stephens |
| 3 | 441 Olivia Creek, Jimmymouth, Georgia... | Michael | Vincent III |
| 4 | 4246 Chelsey Ford Apt. 310, Karamouth, Utah... | Jasmine | Zamora |

There we go. The Name column is gone, and we have split its contents across two new columns.

6.6 Coding challenge

Here's your chance to practice the concepts introduced in this chapter.

6.6.1 Problems

Our customers data set includes an Address column. Each address consists of a street, a city, a state, and a zip code. Your challenge is to separate these four values; assign them to new Street, City, State, and Zip columns; and then remove the Address column. Give the problem a shot, and then review the solution.

6.6.2 Solutions

Our first step is splitting the address strings with a delimiter, using the `split` method. A comma by itself seems to be a good argument:

```
In [56] customers["Address"].str.split(",").head()

Out [56] 0      [6461 Quinn Groves, East Matthew, New Hampshire...
          1      [1360 Tracey Ports Apt. 419, Kyleport, Vermont...
          2      [19120 Fleming Manors, Prestonstad, Montana, ...
          3      [441 Olivia Creek, Jimmymouth, Georgia, 82991]
          4      [4246 Chelsey Ford Apt. 310, Karamouth, Utah...
Name: Address, dtype: object
```

Unfortunately, this split keeps the spaces after the commas. We could perform additional cleanup by using a method such as `strip`, but a better solution is available. If we think about it, each portion of the address is separated by a comma and a space. Therefore, we can pass the `split` method a delimiter of both characters:

```
In [57] customers["Address"].str.split(", ").head()

Out [57] 0      [6461 Quinn Groves, East Matthew, New Hampshire...
          1      [1360 Tracey Ports Apt. 419, Kyleport, Vermont...
          2      [19120 Fleming Manors, Prestonstad, Montana, 2...
          3      [441 Olivia Creek, Jimmymouth, Georgia, 82991]
          4      [4246 Chelsey Ford Apt. 310, Karamouth, Utah, ...
Name: Address, dtype: object
```

Now there is no extra whitespace at the start of each substring within the lists.

By default, the `split` method returns a `Series` of lists. We can make the method return a `DataFrame` by passing the `expand` parameter an argument of `True`:

```
In [58] customers["Address"].str.split(", ", expand = True).head()
```

```
Out [58]
```

| | 0 | 1 | 2 | 3 |
|---|----------------------------|--------------|---------------|-------|
| 0 | 6461 Quinn Groves | East Matthew | New Hampshire | 16656 |
| 1 | 1360 Tracey Ports Apt. 419 | Kyleport | Vermont | 31924 |
| 2 | 19120 Fleming Manors | Prestonstad | Montana | 23495 |
| 3 | 441 Olivia Creek | Jimmymouth | Georgia | 82991 |
| 4 | 4246 Chelsey Ford Apt. 310 | Karamouth | Utah | 76252 |

We have a couple more steps left. Let's add the new four-column DataFrame to our existing customers DataFrame. We'll define a list with the new column names. This time around, let's assign the list to a variable to simplify readability. Next, we'll pass the list in square brackets before an equal sign. On the right side of the equal sign, we'll use the preceding code to create the new DataFrame:

```
In [59] new_cols = ["Street", "City", "State", "Zip"]

customers[new_cols] = customers["Address"].str.split(
    pat = ", ", expand = True
)
```

The last step is deleting the original Address column. The drop method is a good solution here. To alter the DataFrame permanently, make sure to overwrite customers with the returned DataFrame:

```
In [60] customers.drop(labels = "Address", axis = "columns").head()

Out [60]
```

| | First Name | Last Name | Street | City | State | Zip |
|---|------------|-------------|--------------|--------------|--------------|-------|
| 0 | Frank | Manning | 6461 Quin... | East Matthew | New Hamps... | 16656 |
| 1 | Elizabeth | Johnson | 1360 Trac... | Kyleport | Vermont | 31924 |
| 2 | Donald | Stephens | 19120 Fle... | Prestonstad | Montana | 23495 |
| 3 | Michael | Vincent III | 441 Olivi... | Jimmymouth | Georgia | 82991 |
| 4 | Jasmine | Zamora | 4246 Chel... | Karamouth | Utah | 76252 |

Another option is to use Python's built-in `del` keyword before the target column. This syntax mutates the DataFrame:

```
In [61] del customers["Address"]
```

Let's take a look at the final product:

```
In [62] customers.tail()

Out [62]
```

| | First Name | Last Name | Street | City | State | Zip |
|------|------------|-----------|----------------|-------------|---------------|-------|
| 9956 | Dana | Browning | 762 Andrew ... | North Paul | New Mexico | 28889 |
| 9957 | Amanda | Anderson | 44188 Day C... | Lake Marcia | Maine | 37378 |
| 9958 | Eric | Davis | 73015 Miche... | Watsonville | West Virginia | 03933 |
| 9959 | Taylor | Hernandez | 129 Keith G... | Haleyfurt | Oklahoma | 98916 |
| 9960 | Sherry | Nicholson | 355 Griffin... | Davidtown | New Mexico | 17581 |

We've successfully extracted the contents of the Address column to four new columns. Congratulations on completing the coding challenge!

6.7 A note on regular expressions

Any discussion of working with text data is incomplete without mentioning regular expressions, also known as RegEx. A *regular expression* is a search pattern that looks for a sequence of characters within a string.

We declare regular expressions with a special syntax consisting of symbols and characters. `\d`, for example, matches any numeric digit between 0 and 9. With regular

expressions, we can define complex search patterns by targeting lowercase characters, uppercase characters, digits, slashes, whitespace, string boundaries, and more.

Suppose that a phone number like 555-555-5555 is hidden in a larger string. We can use regular expressions to define a search algorithm that extracts sequences of three sequential digits, a dash, three sequential digits, another dash, and four more sequential digits. That level of granularity grants regular expressions their power.

Here's a quick example that shows the syntax in action. The next code sample uses the `replace` method on the `Street` column to swap all occurrences of four sequential digits with an asterisk character:

```
In [63] customers["Street"].head()

Out [63] 0      6461 Quinn Groves
          1    1360 Tracey Ports Apt. 419
          2      19120 Fleming Manors
          3        441 Olivia Creek
          4    4246 Chelsey Ford Apt. 310
Name: Street, dtype: object

In [64] customers["Street"].str.replace(
          "\d{4,}", "*", regex = True
).head()

Out [64] 0      * Quinn Groves
          1    * Tracey Ports Apt. 419
          2      * Fleming Manors
          3        441 Olivia Creek
          4    * Chelsey Ford Apt. 310
Name: Street, dtype: object
```

Regular expressions are a highly specialized technical topic. Whole books are written on the complexities of RegEx. For now, it's important to note that pandas supports RegEx arguments for most of its string methods. You can check out appendix E for a more comprehensive introduction to the domain.

Summary

- The `str` attribute holds a `StringMethods` object with methods for performing string manipulations on `Series` values.
- The `strip` family of methods removes whitespace from the start of a string, the end of a string, or both sides.
- Methods such as `upper`, `lower`, `capitalize`, and `title` modify the letter casing of string characters.
- The `contains` method checks for the presence of a substring within another string.
- The `startswith` method checks for a substring at the beginning of a string.
- The complementary `endswith` method checks for a substring at the end of a string.
- The `split` method splits a string into a list by using a specified delimiter. We can use it to split a `DataFrame` column's text across several `Series`.



MultiIndex DataFrames

This chapter covers

- Creating a `MultiIndex`
- Selecting rows and columns from a `MultiIndex DataFrame`
- Extracting a cross-section from a `MultiIndex DataFrame`
- Swapping `MultiIndex` levels

So far on our pandas journey, we've explored the one-dimensional `Series` and the two-dimensional `DataFrame`. The number of dimensions is the number of reference points we need to extract a value from a data structure. We need only one label or one index position to locate a value in a `Series`. We need two reference points to locate a value in a `DataFrame`: a label/index for the rows and a label/index for the columns. Can we expand beyond two dimensions? Absolutely! Pandas supports data sets with any number of dimensions through the use of a `MultiIndex`.

A `MultiIndex` is an index object that holds multiple levels. Each level stores a value for the row. It is optimal to use a `MultiIndex` when a combination of values

| Stock | Date | Price |
|-------|------------|----------|
| MSFT | 02/08/2021 | 793.60 |
| MSFT | 02/09/2021 | 1,408.38 |
| GOOG | 02/08/2021 | 565.81 |
| GOOG | 02/09/2021 | 17.62 |

Figure 7.1 Sample data set with Stock, Date, and Price columns

provides the best identifier for a row of data. Consider the data set in figure 7.1, which stores stock prices across multiple dates.

Suppose that we want to find a unique identifier for each price. Neither a stock's name nor its date is sufficient by itself, but the combination of both values is a good fit. The stock "MSFT" appears twice, the date "02/08/2021" appears twice, but the combination of "MSFT" and "02/08/2021" appears only once. A MultiIndex storing the values of the Stock and Date columns would suit this data set well.

A MultiIndex is also ideal for *hierarchical* data—data in which one column's values are a subcategory of another column's values. Consider the data set in figure 7.2.

| Group | Item | Calories |
|-----------|----------|----------|
| Fruit | Apple | 95 |
| Fruit | Banana | 105 |
| Vegetable | Broccoli | 50 |
| Vegetable | Tomato | 22 |

Figure 7.2 Sample data set with Group, Item, and Calories columns

The Item column's values are subcategories of the Group column's values. An Apple is a type of Fruit, and Broccoli is a type of Vegetable. Thus, the Group and Item columns could serve as a MultiIndex combo.

The MultiIndex is an obscure feature in pandas but one that's worth taking the time to learn. The introduction of multiple index levels adds a lot of versatility to how we slice and dice data sets.

7.1 *The MultiIndex object*

Let's open a new Jupyter Notebook, import the pandas library, and assign it the alias pd:

```
In [1] import pandas as pd
```

To keep things simple, we'll start by creating a MultiIndex object from scratch. In section 7.2, we'll practice these concepts on an imported data set.

Do you recall Python's built-in tuple object? The tuple is an immutable data structure that holds a sequence of values in order. A tuple is effectively a list that cannot be modified after creation. For a deeper dive into this data structure, see appendix B.

Let's say we want to model a street address. An address typically includes a street name, city, town, and zip code. We could store these four elements in a tuple:

```
In [2] address = ("8809 Flair Square", "Toddsdie", "IL", "37206")
address
```

```
Out [2] ('8809 Underwood Squares', 'Toddsdie', 'IL', '37206')
```

Series and DataFrame indices can hold various data types: strings, numbers, datetimes, and more. But all these objects can store only one value per index position, one label per row. A tuple doesn't have that limitation.

What if we gathered multiple tuples in a list? The list would look like this:

```
In [3] addresses = [
    ("8809 Flair Square", "Toddsdie", "IL", "37206"),
    ("9901 Austin Street", "Toddsdie", "IL", "37206"),
    ("905 Hogan Quarter", "Franklin", "IL", "37206"),
]
```

Now imagine these tuples serving as a DataFrame's index labels. I hope that the idea is not too confusing. All operations remain the same. We would still be able to reference a row by its index label, but each index label would be a container holding multiple elements. That's a good way to start thinking about the MultiIndex object—as an index in which each label can store multiple pieces of data.

We can create a MultiIndex object independently of a Series or DataFrame. The MultiIndex class is available as a top-level attribute on the pandas library. It includes a `from_tuples` class method that instantiates a MultiIndex from a list of tuples. A *class method* is a method we invoke on a class rather than an instance. The next example invokes the `from_tuples` class method and passes it the `addresses` list:

```
In [4] # The two lines below are equivalent
pd.MultiIndex.from_tuples(addresses)
pd.MultiIndex.from_tuples(tuples = addresses)

Out [4] MultiIndex([( '8809 Flair Square',      'Toddsdie', 'IL', '37206'),
                    ('9901 Austin Street',      'Toddsdie', 'IL', '37206'),
                    (' 905 Hogan Quarter',     'Franklin',  'IL', '37206')],
```

We have our first MultiIndex, which stores three tuples of four elements each. There is a consistent pattern to each tuple's elements:

- The first value is the address.
- The second value is the city.
- The third value is the state.
- The fourth value is the zip code.

In pandas terminology, the collection of tuple values at the same position forms a *level* of the MultiIndex. In the previous example, the first MultiIndex level consists of the values "8809 Flair Square", "9901 Austin Street", and "905 Hogan

`Quarter".` Similarly, the second MultiIndex level consists of "Toddsdie", "Toddsdie", and "Franklin".

We can assign each MultiIndex level a name by passing a list to the `from_tuples` method's `names` parameter. Here, we assign the names "Street", "City", "State", and "Zip":

```
In [5] row_index = pd.MultiIndex.from_tuples(
    tuples = addresses,
    names = ["Street", "City", "State", "Zip"]
)

row_index

Out [5] MultiIndex([( '8809 Flair Square',    'Toddsdie', 'IL', '37206'),
                   ('9901 Austin Street',    'Toddsdie', 'IL', '37206'),
                   (' 905 Hogan Quarter',   'Franklin', 'IL', '37206')], names=['Street', 'City', 'State', 'Zip'])
```

To summarize, a MultiIndex is a storage container in which each label holds multiple values. A level consists of the values at the same position across the labels.

Now that we have a MultiIndex, let's attach it to a DataFrame. The easiest way is to use the DataFrame constructor's `index` parameter. We passed this parameter a list of strings in earlier chapters, but it also accepts any valid index object. Let's pass it the MultiIndex we assigned to the `row_index` variable. Because our MultiIndex has three tuples (or, equivalently, three labels), we'll need to provide three rows of data:

```
In [6] data = [
    ["A", "B+"],
    ["C+", "C"],
    ["D-", "A"],
]

columns = ["Schools", "Cost of Living"]

area_grades = pd.DataFrame(
    data = data, index = row_index, columns = columns
)

area_grades

Out [6]
```

| | | | | | Schools | Cost of Living |
|--------------------|----------|-------|-------|----|---------|----------------|
| Street | City | State | Zip | | | |
| 8809 Flair Square | Toddsdie | IL | 37206 | A | B+ | |
| 9901 Austin Street | Toddsdie | IL | 37206 | C+ | C | |
| 905 Hogan Quarter | Franklin | IL | 37206 | D- | A | |

We have a DataFrame with a MultiIndex on its row axis. Each row's label holds four values: a street, a city, a state, and a zip code.

Let's turn our focus to the column axis. Pandas stores a DataFrame's column headers in an `index` object as well. We can access that `index` via the `columns` attribute:

```
In [7] area_grades.columns
Out [7] Index(['Schools', 'Cost of Living'], dtype='object')
```

Pandas currently stores the two column names in a single-level `Index` object. Let's create a second `MultiIndex` and attach it to the column axis. The next example invokes the `from_tuples` class method again, passing it a list of four tuples. Each tuple holds two strings:

```
In [8] column_index = pd.MultiIndex.from_tuples(
    [
        ("Culture", "Restaurants"),
        ("Culture", "Museums"),
        ("Services", "Police"),
        ("Services", "Schools"),
    ]
)
column_index

Out [8] MultiIndex([( 'Culture', 'Restaurants'),
                    ( 'Culture', 'Museums'),
                    ('Services', 'Police'),
                    ('Services', 'Schools')],
```

Let's attach both of our `MultiIndex`es to a `DataFrame`. The `MultiIndex` for the row axis (`row_index`) requires the data set to hold three rows. The `MultiIndex` for the column axis (`column_index`) requires the data set to hold four columns. Therefore, our data set must have a 3×4 shape. Let's create that sample data. The next example declares a list of three lists. Each nested list stores four strings:

```
In [9] data = [
    ["C-", "B+", "B-", "A"],
    ["D+", "C", "A", "C+"],
    ["A-", "A", "D+", "F"]
]
```

We're ready to put the pieces together and create a `DataFrame` with a `MultiIndex` on both the row and column axes. In the `DataFrame` constructor, let's pass our respective `MultiIndex` variables to the `index` and `columns` parameters:

```
In [10] pd.DataFrame(
    data = data, index = row_index, columns = column_index
)
Out [10]
```

| Street | City | State | Zip | Culture | | Services | |
|--------------|----------|-------|-------|-------------|---------|----------|---------|
| | | | | Restaurants | Museums | Police | Schools |
| 8809 Flai... | Toddsdie | IL | 37206 | C- | B+ | B- | A |
| 9901 Aust... | Toddsdie | IL | 37206 | D+ | C | A | C+ |
| 905 Hogan... | Franklin | IL | 37206 | A- | A | D+ | F |

Hooray! We've successfully created a DataFrame with a four-level row MultiIndex and a two-level column MultiIndex. A MultiIndex is an index that can store multiple levels, multiple tiers. Each index label is made of multiple components. That's all there is to it.

7.2 *MultiIndex DataFrames*

Let's scale things up a bit. The neighborhoods.csv data set is similar to the one we created in section 7.1; it's a listing of ~250 fictional addresses in cities across the United States. Each address is graded on four characteristics of livability: Restaurants, Museums, Police, and Schools. The four grades are grouped in two parent categories: Culture and Services.

Here's a preview of the first couple of rows of the raw CSV file. In a CSV, a comma separates every two subsequent values in a row of data. Thus, the presence of sequential commas with nothing between them indicates missing values:

```
,,Culture,Culture,Services,Services
,,,Restaurants,Museums,Police,Schools
State,City,Street,,,
MO,Fisherborough,244 Tracy View,C+,F,D-,A+
```

How will pandas import this CSV file's data? Let's find out with the `read_csv` function:

```
In [11] neighborhoods = pd.read_csv("neighborhoods.csv")
        neighborhoods.head()

Out [11]
```

| | Unnamed: 0 | Unnamed: 1 | Unnamed: 2 | Culture | Culture.1 | Services | Services.1 |
|---|------------|------------|------------|-----------|-----------|----------|------------|
| 0 | NaN | NaN | NaN | Restau... | Museums | Police | Schools |
| 1 | State | City | Street | NaN | NaN | NaN | NaN |
| 2 | MO | Fisher... | 244 Tr... | C+ | F | D- | A+ |
| 3 | SD | Port C... | 446 Cy... | C- | B | B | D+ |
| 4 | WV | Jimene... | 432 Jo... | A | A+ | F | B |

Something is off here! First, we have three Unnamed columns, each one ending in a different number. When importing a CSV, pandas assumes that the file's first row holds the column names, also known as the headers. If a header slot does not have a value, pandas assigns a title of "Unnamed" to the column. Simultaneously, the library tries to avoid duplicate column names. To distinguish between multiple missing headers, the library adds a numerical index to each. Thus, we have three Unnamed columns: Unnamed: 0, Unnamed: 1, and Unnamed: 2.

The four columns to the right have the same naming issue. Notice that pandas assigns a title of Culture to the column at index 3 and Culture 1 to the one after it. The CSV file has the same value of "Culture" for two header cells in a row, followed by the same value of "Services" for two header cells in a row.

Unfortunately, that's not the end of our problems. In row 0, each of the first three columns holds a `NaN` value. In row 1, we have `NaN` values present in the last four columns. The issue is that the CSV is trying to model a multilevel row index and a

multilevel column index, but the default arguments to the `read_csv` function's parameters don't recognize it. Luckily, we can solve this problem by altering the arguments to a couple of `read_csv` parameters.

First, we have to tell pandas that the three leftmost columns should serve as the index of the DataFrame. We can do this by passing the `index_col` parameter a list of numbers, each one representing the index (or numeric position) of a column that should be in the DataFrame's index. The index starts counting from 0. Thus, the first three columns (the Unnamed ones) will have index positions 0, 1, and 2. When we pass `index_col` a list with multiple values, pandas automatically creates a MultiIndex for the DataFrame:

```
In [12] neighborhoods = pd.read_csv(
    "neighborhoods.csv",
    index_col = [0, 1, 2]
)
neighborhoods.head()
```

Out [12]

| | | | Culture | Culture.1 | Services | Services.1 |
|-------|--------------|----------------|-------------|-----------|----------|------------|
| NaN | NaN | NaN | Restaurants | Museums | Police | Schools |
| State | City | Street | | | | |
| MO | Fisherbor... | 244 Tracy... | C+ | F | D- | A+ |
| SD | Port Curt... | 446 Cynthia... | C- | B | B | D+ |
| WV | Jimenezview | 432 John ... | A | A+ | F | B |

We're halfway there. Next, we need to tell pandas which data set rows we'd like to use for our DataFrame's headers. The `read_csv` function assumes that only the first row will hold the headers. In this data set, the first two rows will hold the headers. We can customize the DataFrame headers with the `read_csv` function's `header` parameter, which accepts a list of integers representing the *rows* that pandas should set as column headers. If we provide a list with more than one element, pandas will assign a MultiIndex to the columns. The next example sets the first two rows (indexes 0 and 1) as column headers:

```
In [13] neighborhoods = pd.read_csv(
    "neighborhoods.csv",
    index_col = [0, 1, 2],
    header = [0, 1]
)
neighborhoods.head()
```

Out [13]

| | | | Culture | | Services | |
|-------|-----------------|-----------------|-------------|---------|----------|---------|
| | | | Restaurants | Museums | Police | Schools |
| State | City | Street | | | | |
| MO | Fisherborough | 244 Tracy View | C+ | F | D- | A+ |
| SD | Port Curtisv... | 446 Cynthia ... | C- | B | B | D+ |
| WV | Jimenezview | 432 John Common | A | A+ | F | B |
| AK | Stevenshire | 238 Andrew Rue | D- | A | A- | A- |
| ND | New Joshuaport | 877 Walter Neck | D+ | C- | B | B |

Now we have something we can work with!

As mentioned earlier, the data set groups four characteristics of livability (Restaurants, Museums, Police, and Schools) in two categories (Culture and Services). When we have a parent category encompassing smaller child categories, creating a MultiIndex is an optimal way to enable quick slicing.

Let's invoke some familiar methods to observe how the output changes with a MultiIndex DataFrame. The `info` method is a good place to start:

```
In [14] neighborhoods.info()

Out [14]

<class 'pandas.core.frame.DataFrame'>
MultiIndex: 251 entries, ('MO', 'Fisherborough', '244 Tracy View') to ('NE',
   'South Kennethmouth', '346 Wallace Pass')
Data columns (total 4 columns):
 #   Column           Non-Null Count  Dtype  
---  --  
 0   (Culture, Restaurants) 251 non-null    object 
 1   (Culture, Museums)     251 non-null    object 
 2   (Services, Police)    251 non-null    object 
 3   (Services, Schools)   251 non-null    object 
dtypes: object(4)
memory use: 27.2+ KB
```

Notice that pandas prints each column's name as a two-element tuple, such as (Culture, Restaurants). Similarly, the library stores each row's label as a three-element tuple, such as ('MO', 'Fisherborough', '244 Tracy View').

We can access the rows' MultiIndex object with the familiar `index` attribute. The output allows us to see the tuples that hold each row's values:

```
In [15] neighborhoods.index

Out [15] MultiIndex([
        ('MO', 'Fisherborough', '244 Tracy View'),
        ('SD', 'Port Curtissville', '446 Cynthia Inlet'),
        ('WV', 'Jimenezview', '432 John Common'),
        ('AK', 'Stevenshire', '238 Andrew Rue'),
        ('ND', 'New Joshuaport', '877 Walter Neck'),
        ('ID', 'Wellsville', '696 Weber Stravenue'),
        ('TN', 'Jodiburgh', '285 Justin Corners'),
        ('DC', 'Lake Christopher', '607 Montoya Harbors'),
        ('OH', 'Port Mike', '041 Michael Neck'),
        ('ND', 'Hardyburgh', '550 Gilmore Mountains'),
        ...
        ('AK', 'South Nicholasshire', '114 Jones Garden'),
        ('IA', 'Port Willieport', '320 Jennifer Mission'),
        ('ME', 'Port Linda', '692 Hill Glens'),
        ('KS', 'Kaylamouth', '483 Freeman Via'),
        ('WA', 'Port Shawnfort', '691 Winters Bridge'),
        ('MI', 'North Matthew', '055 Clayton Isle'),
        ('MT', 'Chadton', '601 Richards Road'),
        ('SC', 'Diazmouth', '385 Robin Harbors'),
        ('VA', 'Laurentown', '255 Gonzalez Land'),
        ('NE', 'South Kennethmouth', '346 Wallace Pass')],
       names=['State', 'City', 'Street'], length=251)
```

We can access the columns' MultiIndex object with the `columns` attribute, which also uses tuples to store the nested column labels:

```
In [16] neighborhoods.columns

Out [16] MultiIndex([( 'Culture', 'Restaurants'),
                      ('Culture', 'Museums'),
                      ('Services', 'Police'),
                      ('Services', 'Schools')],
```

Under its hood, pandas composes a MultiIndex from multiple Index objects. When importing the data set, the library assigned a name to each Index from a CSV header. We can access the list of index names with the `names` attribute on the MultiIndex object. State, City, and Street are the names of the three CSV columns that became our index:

```
In [17] neighborhoods.index.names

Out [17] FrozenList(['State', 'City', 'Street'])
```

Pandas assigns an order to each nested level within the MultiIndex. In our current neighborhoods DataFrame,

- The State level has an index position of 0.
- The City level has an index position of 1.
- The Street level has an index position of 2.

The `get_level_values` method extracts the Index object at a given level of the MultiIndex. We can pass either the level's index position or the level's name to the method's first and only parameter, `level`:

```
In [18] # The two lines below are equivalent
       neighborhoods.index.get_level_values(1)
       neighborhoods.index.get_level_values("City")

Out [18] Index(['Fisherborough', 'Port Curtisville', 'Jimenezview',
                'Stevenshire', 'New Joshuaport', 'Wellsville', 'Jodiburgh',
                'Lake Christopher', 'Port Mike', 'Hardyburgh',
                ...
                'South Nicholasshire', 'Port Willieport', 'Port Linda',
                'Kaylamouth', 'Port Shawnfort', 'North Matthew', 'Chadton',
                'Diazmouth', 'Laurentown', 'South Kennethmouth'],
                dtype='object', name='City', length=251)
```

The columns' MultiIndex levels do not have any names because the CSV did not provide any:

```
In [19] neighborhoods.columns.names

Out [19] FrozenList([None, None])
```

Let's fix this problem. We can access the columns' MultiIndex with the `columns` attribute. Then we can assign a new list of column names to the `names` attribute of the

MultiIndex object. The names "Category" and "Subcategory" seem to be fitting here:

```
In [20] neighborhoods.columns.names = ["Category", "Subcategory"]
neighborhoods.columns.names

Out [20] FrozenList(['Category', 'Subcategory'])
```

The level names will appear to the left of the column headers in the output. Let's invoke the head method to see the difference:

```
In [21] neighborhoods.head(3)
```

```
Out [21]
```

| Category | | Culture | | Services | |
|-------------|--------------|--------------|---------|----------|---------|
| Subcategory | | Restaurants | Museums | Police | Schools |
| State | City | Street | | | |
| MO | Fisherbor... | 244 Tracy... | C+ | F | D- |
| SD | Port Curt... | 446 Cynth... | C- | B | B |
| WV | Jimenezview | 432 John ... | A | A+ | F |
| | | | | | B |

Now that we've assigned names to the levels, we can use the `get_level_values` method to retrieve any Index from the columns' MultiIndex. Remember that we can pass either the column's index position or its name to the method:

```
In [22] # The two lines below are equivalent
neighborhoods.columns.get_level_values(0)
neighborhoods.columns.get_level_values("Category")

Out [22] Index(['Culture', 'Culture', 'Services', 'Services'],
dtype='object', name='Category')
```

A MultiIndex will carry over to new objects derived from a data set. The index can switch axes depending on the operation. Consider a DataFrame's `nunique` method, which returns a Series with a count of unique values per column. If we invoke `nunique` on `neighborhoods`, the DataFrame's column MultiIndex will swap axes and serve as the row's MultiIndex in the resulting Series:

```
In [23] neighborhoods.head(1)
```

```
Out [23]
```

| Category | | Culture | | Services | |
|-------------|----------------|-----------------|---------|----------|---------|
| Subcategory | | Restaurants | Museums | Police | Schools |
| State | City | Street | | | |
| AK | Rowlandchester | 386 Rebecca ... | C- | A- | A+ |
| | | | | | C |

```
In [24] neighborhoods.nunique()
```

```
Out [24] Culture    Restaurants      13
                  Museums       13
```

```
Services    Police        13
          Schools       13
dtype: int64
```

The MultiIndex Series tells us how many unique values pandas found in each of the four columns. The values are equal in this case because all four columns hold the 13 possible grades (A+ to F).

7.3 Sorting a MultiIndex

Pandas can find a value in an ordered collection much quicker than in a jumbled one. A good analogous example is searching for a word in a dictionary. It's easier to locate a word when words are in alphabetical order rather than a random sequence. Thus, it's optimal to sort an index before selecting any rows and columns from a DataFrame.

Chapter 4 introduced the `sort_index` method for sorting a DataFrame. When we invoke the method on a MultiIndex DataFrame, pandas sorts all levels in ascending order and proceeds from the outside in. In the next example, pandas sorts the State-level values first, then the City-level values, and finally the Street-level values:

```
In [25] neighborhoods.sort_index()
```

```
Out [25]
```

| Category | | | Culture | | | Services | |
|-------------|----------------|--------|---------------------|-------|--------|----------|-----|
| Subcategory | | | Restaurants Museums | | Police | Schools | |
| State | City | Street | | | | | |
| AK | Rowlandchester | 386 | Rebecca | ... | C- | A- | A+ |
| | Scottstad | 082 | Leblanc | ... | D | C- | D |
| | | 114 | Jones | Ga... | D- | D- | D |
| | Stevenshire | 238 | Andrew Rue | | D- | A | A- |
| AL | Clarkland | 430 | Douglas | ... | A | F | C+ |
| ... | ... | ... | ... | ... | ... | ... | ... |
| WY | Lake Nicole | 754 | Weaver T... | | B | D- | B |
| | | 933 | Jennifer... | | C | A+ | A- |
| | Martintown | 013 | Bell Mills | | C- | D | A- |
| | Port Jason | 624 | Faulkner... | | A- | F | C+ |
| | Reneeshire | 717 | Patel Sq... | | B | B+ | D |

251 rows × 4 columns

Let's make sure that we understand the output. First, pandas targets the State level and sorts the value "AK" before "AL". Then, within the state of "AK", pandas sorts the city of "Rowlandchester" before "Scottstad". It applies the same logic to the final level, Street.

The `sort_values` method includes an `ascending` parameter. We can pass the parameter a Boolean to apply a consistent sort order to all MultiIndex levels. The next example provides an argument of `False`. Pandas sorts the State values in reverse alphabetical order, then the City values in reverse alphabetical order, and finally the Street values in reverse alphabetical order:

```
In [26] neighborhoods.sort_index(ascending = False).head()
```

```
Out [26]
```

| Category | Subcategory | State | City | Culture | | Services | |
|----------|-------------|-----------------|------|---------------------|----|----------------|----|
| | | | | Restaurants Museums | | Police Schools | |
| | | | | Street | | | |
| WY | Reneeshire | 717 Patel Sq... | | B | B+ | D | A |
| | Port Jason | 624 Faulkner... | | A- | F | C+ | C+ |
| | Martintown | 013 Bell Mills | | C- | D | A- | B- |
| | Lake Nicole | 933 Jennifer... | | C | A+ | A- | C |
| | | 754 Weaver T... | | B | D- | B | D |

Suppose that we want to vary the sort order for different levels. We can pass the ascending parameter a list of Booleans. Each Boolean sets the sort order for the next MultiIndex level, starting with the outermost one and proceeding inward. An argument of [True, False, True], for example, will sort the State level in ascending order, the City level in descending order, and the Street level in ascending order:

```
In [27] neighborhoods.sort_index(ascending = [True, False, True]).head()
```

```
Out [27]
```

| Category | Subcategory | State | City | Culture | | Services | |
|----------|----------------|-----------------|------|---------------------|----|----------------|----|
| | | | | Restaurants Museums | | Police Schools | |
| | | | | Street | | | |
| AK | Stevenshire | 238 Andrew Rue | | D- | A | A- | A- |
| | Scottstad | 082 Leblanc ... | | D | C- | D | B+ |
| | | 114 Jones Ga... | | D- | D- | D | D |
| | Rowlandchester | 386 Rebecca ... | | C- | A- | A+ | C |
| AL | Vegaside | 191 Mindy Me... | | B+ | A- | A+ | D+ |

We can also sort a MultiIndex level by itself. Let's say we want to sort the rows by the values in the second MultiIndex level, City. We can pass the level's index position or its name to the level parameter of the sort_index method. Pandas will ignore the remaining levels when sorting:

```
In [28] # The two lines below are equivalent
neighborhoods.sort_index(level = 1)
neighborhoods.sort_index(level = "City")
```

```
Out [28]
```

| Category | Subcategory | State | City | Culture | | Services | |
|----------|-------------|-----------------|------|---------------------|-----|----------------|-----|
| | | | | Restaurants Museums | | Police Schools | |
| | | | | Street | | | |
| AR | Allisonland | 124 Diaz Brooks | | C- | A+ | F | C+ |
| GA | Amyburgh | 941 Brian Ex... | | B | B | D- | C+ |
| IA | Amyburgh | 163 Heather ... | | F | D | A+ | A- |
| ID | Andrewshire | 952 Ellis Drive | | C+ | A- | C+ | A |
| UT | Baileyfort | 919 Stewart ... | | D+ | C+ | A | C |
| ... | ... | ... | | ... | ... | ... | ... |
| NC | West Scott | 348 Jack Branch | | A- | D- | A- | A |

```
SD    West Scott      139 Hardy Vista      C+      A-      D+      B-
IN    Wilsonborough  066 Carr Road        A+      C-      B       F
NC    Wilsonshire     871 Christop...      B+      B       D+      F
NV    Wilsonshire     542 Jessica ...      A       A+      C-      C+

```

251 rows × 4 columns

The level parameter also accepts a list of levels. The next example sorts the City level's values first, followed by the Street level's values. The State level's values do not influence the sort at all:

```
In [29] # The two lines below are equivalent
neighborhoods.sort_index(level = [1, 2]).head()
neighborhoods.sort_index(level = ["City", "Street"]).head()
```

Out [29]

| Category | Subcategory | State | City | Street | Culture | | Services | |
|----------|-------------|-------------|--------|--------|---------------------|----------|----------------|---------|
| | | | | | Restaurants Museums | | Police Schools | |
| | | | | | Culture | Services | Police | Schools |
| AR | Allisonland | 124 Diaz | Brooks | | C- | A+ | F | C+ |
| IA | Amyburgh | 163 Heather | ... | | F | D | A+ | A- |
| GA | Amyburgh | 941 Brian | Ex... | | B | B | D- | C+ |
| ID | Andrewshire | 952 Ellis | Drive | | C+ | A- | C+ | A |
| VT | Baileyfort | 831 Norma | Cove | | B | D+ | A+ | D+ |

We can also combine the ascending and level parameters. Notice in the preceding example that pandas sorted the two Street values for the city of Amyburgh ("163 Heather Neck" and "941 Brian Expressway") in alphabetical/ascending order. The next example sorts the City level in ascending order and the Street level in descending order, thus swapping the positions of the two Amyburgh Street values:

```
In [30] neighborhoods.sort_index(
        level = ["City", "Street"], ascending = [True, False]
).head()
```

Out [30]

| Category | Subcategory | State | City | Street | Culture | | Services | |
|----------|-------------|-------------|--------|--------|---------------------|----------|----------------|---------|
| | | | | | Restaurants Museums | | Police Schools | |
| | | | | | Culture | Services | Police | Schools |
| AR | Allisonland | 124 Diaz | Brooks | | C- | A+ | F | C+ |
| GA | Amyburgh | 941 Brian | Ex... | | B | B | D- | C+ |
| IA | Amyburgh | 163 Heather | ... | | F | D | A+ | A- |
| ID | Andrewshire | 952 Ellis | Drive | | C+ | A- | C+ | A |
| UT | Baileyfort | 919 Stewart | ... | | D+ | C+ | A | C |

We can sort the columns' MultiIndex as well by supplying an axis parameter to the sort_index method. The parameter's default argument is 0, which represents the row index. To sort the columns, we can pass either the number 1 or the string "columns". In the next example, pandas sorts the Category level first and the Subcategory level second. The value Culture comes before Services. Within the Culture level,

the value Museums comes before Restaurants. Within Services, the value Police comes before Schools:

```
In [31] # The two lines below are equivalent
neighborhoods.sort_index(axis = 1).head(3)
neighborhoods.sort_index(axis = "columns").head(3)
```

Out [31]

| Category | Subcategory | State | City | Culture | | Services | |
|----------|----------------|-------|-------------|---------|-------------|----------|---------|
| | | | | Museums | Restaurants | Police | Schools |
| | | | | Street | | | |
| MO | Fisherborough | 244 | Tracy View | | F | C+ | D- |
| SD | Port Curtis... | 446 | Cynthia ... | | B | C- | B |
| WV | Jimenezview | 432 | John Common | | A+ | A | F |

We can combine the level and ascending parameters with the axis parameter to further customize the columns' sort orders. The next example sorts the Subcategory level values in descending order. Pandas ignores the values in the Category level. The reverse alphabetical order of the subcategories ("Schools", "Restaurants", "Police", and "Museums") forces a visual breakup of the Category group. Thus, the output prints the Services and Culture column headers multiple times:

```
In [32] neighborhoods.sort_index(
    axis = 1, level = "Subcategory", ascending = False
).head(3)
```

Out [32]

| Category | Subcategory | State | City | Services | | Culture | |
|----------|----------------|-------|-------------|----------|-------------|---------|---------|
| | | | | Schools | Restaurants | Police | Museums |
| | | | | Street | | | |
| MO | Fisherborough | 244 | Tracy View | | A+ | C+ | D- |
| SD | Port Curtis... | 446 | Cynthia ... | | D+ | C- | B |
| WV | Jimenezview | 432 | John Common | | B | A | F |

In section 7.4, we'll learn how to extract rows and columns from a MultiIndex DataFrame with familiar accessor attributes such as `loc` and `iloc`. As mentioned earlier, it's optimal to sort our index before we look up any row. Let's sort the MultiIndex levels in ascending order and overwrite our neighborhoods DataFrame:

```
In [33] neighborhoods = neighborhoods.sort_index(ascending = True)
```

Here's the result:

```
In [34] neighborhoods.head(3)
```

Out [34]

| Category | Subcategory | State | City | Culture | | Services | |
|----------|----------------|-------|-------------|-------------|---------|----------|---------|
| | | | | Restaurants | Museums | Police | Schools |
| | | | | Street | | | |
| AK | Rowlandchester | 386 | Rebecca ... | | C- | A- | A+ |
| | Scottstad | 082 | Leblanc ... | | D | C- | D |
| | | 114 | Jones Ga... | | D- | D- | D |

Looks good. We've sorted each level in the MultiIndex and are clear to proceed.

7.4 Selecting with a MultiIndex

Extracting DataFrame rows and columns gets tricky when multiple levels are involved. The key question to ask before writing any code is what we want to pull out.

Chapter 4 introduced the square-bracket syntax for selecting a column from a DataFrame. Here's a quick reminder. The following code creates a DataFrame with two rows and two columns:

```
In [35]: data = [
    [1, 2],
    [3, 4]
]

df = pd.DataFrame(
    data = data, index = ["A", "B"], columns = ["X", "Y"]
)

df

Out [35]:
      X  Y
A  1  2
B  3  4
```

The square-bracket syntax extracts a column from the DataFrame as a Series:

```
In [36]: df["X"]

Out [36]: A    1
           B    3
           Name: X, dtype: int64
```

Suppose that we want to pull out a column from neighborhoods. Each of the four columns in the DataFrame requires a combination of two identifiers: a Category and a Subcategory. What happens if we pass only one?

7.4.1 Extracting one or more columns

If we pass a single value in square brackets, pandas will look for it in the outermost level of the columns' MultiIndex. The following example searches for "Services", which is a valid value in the Category level:

```
In [37]: neighborhoods["Services"]

Out [37]:
      Subcategory          Police   Schools
      State City        Street
AK      Rowlandchester  386 Rebecca Cove     A+      C
                  Scottstad   082 Leblanc Freeway    D      B+
                               114 Jones Garden     D      D
                  Stevenshire   238 Andrew Rue     A-      A-
```

| | | | | |
|-----|-------------|----------------------|-----|-----|
| AL | Clarkland | 430 Douglas Mission | C+ | B+ |
| ... | ... | ... | ... | ... |
| WY | Lake Nicole | 754 Weaver Turnpike | B | D |
| | | 933 Jennifer Burg | A- | C |
| | Martintown | 013 Bell Mills | A- | B- |
| | Port Jason | 624 Faulkner Orchard | C+ | C+ |
| | Reneeshire | 717 Patel Square | D | A |

251 rows × 2 columns

Notice that the new DataFrame does not have a Category level. It has a plain Index with two values: "Police" and "Schools". There is no longer a need for a MultiIndex; the two columns in this DataFrame are the subcategories that fall under the Services value. The Category level no longer has any variation that merits listing.

Pandas will raise a `KeyError` exception if the value does not exist in the outermost level of the columns' MultiIndex:

```
In [38] neighborhoods["Schools"]
```

```
-----
KeyError                                                 Traceback (most recent call last)
KeyError: 'Schools'
```

What if we want to target a specific Category and then a Subcategory within it? To specify values across multiple levels in the column's MultiIndex, we can pass them inside a tuple. The next example targets the column with a value of "Services" in the Category level and a value of "Schools" in the Subcategory level:

```
In [39] neighborhoods[("Services", "Schools")]
```

```
Out [39] State City          Street
      AK Rowlandchester 386 Rebecca Cove      C
           Scottstad     082 Leblanc Freeway    B+
                   114 Jones Garden      D
           Stevenshire    238 Andrew Rue       A-
      AL Clarkland      430 Douglas Mission   B+
                   ...
      WY Lake Nicole     754 Weaver Turnpike   D
                   933 Jennifer Burg      C
           Martintown     013 Bell Mills       B-
           Port Jason      624 Faulkner Orchard  C+
           Reneeshire     717 Patel Square      A
Name: (Services, Schools), Length: 251, dtype: object
```

The method returns a Series without a column index! Once again, when we provide a value for a MultiIndex level, we remove the need for that level to exist. We explicitly told pandas what values to target in the Category and Subcategory levels, so the library removed the two levels from the column index. Because the ("Services", "Schools") combination yielded a single column of data, pandas returned a Series object.

To extract multiple DataFrame columns, we need to pass the square brackets a list of tuples. Each tuple should specify the level values for one column. The order of tuples within the list sets the order of columns in the resulting DataFrame. The next example pulls out two columns from neighborhoods:

```
In [40]: neighborhoods[["Services", "Schools"), ("Culture", "Museums")]]
```

```
Out [40]
```

| Category | | Services Culture | | | |
|-------------|----------------|----------------------|-----|---------|-----|
| Subcategory | | Schools | | Museums | |
| State | City | Street | | | |
| AK | Rowlandchester | 386 Rebecca Cove | C | A- | |
| | Scottstad | 082 Leblanc Freeway | B+ | C- | |
| | | 114 Jones Garden | D | D- | |
| AL | Stevenshire | 238 Andrew Rue | A- | A | |
| | Clarkland | 430 Douglas Mission | B+ | F | |
| | ... | ... | ... | ... | ... |
| WY | Lake Nicole | 754 Weaver Turnpike | D | D- | |
| | | 933 Jennifer Burg | C | A+ | |
| | Martintown | 013 Bell Mills | B- | D | |
| | Port Jason | 624 Faulkner Orchard | C+ | F | |
| | Reneeshire | 717 Patel Square | A | B+ | |

```
251 rows × 2 columns
```

Syntax tends to become confusing and error-prone when it involves multiple parentheses and brackets. We can simplify the preceding code by assigning the list to a variable and breaking its tuples across several lines:

```
In [41]: columns = [
    ("Services", "Schools"),
    ("Culture", "Museums")
]
neighborhoods[columns]
```

```
Out [41]
```

| Category | | Services Culture | | | |
|-------------|----------------|----------------------|-----|---------|-----|
| Subcategory | | Schools | | Museums | |
| State | City | Street | | | |
| AK | Rowlandchester | 386 Rebecca Cove | C | A- | |
| | Scottstad | 082 Leblanc Freeway | B+ | C- | |
| | | 114 Jones Garden | D | D- | |
| AL | Stevenshire | 238 Andrew Rue | A- | A | |
| | Clarkland | 430 Douglas Mission | B+ | F | |
| | ... | ... | ... | ... | ... |
| WY | Lake Nicole | 754 Weaver Turnpike | D | D- | |
| | | 933 Jennifer Burg | C | A+ | |
| | Martintown | 013 Bell Mills | B- | D | |
| | Port Jason | 624 Faulkner Orchard | C+ | F | |
| | Reneeshire | 717 Patel Square | A | B+ | |

```
251 rows × 2 columns
```

The previous two examples accomplish the same result, but this code is significantly easier to read; its syntax clearly identifies where each tuple begins and ends.

7.4.2 **Extracting one or more rows with loc**

Chapter 4 introduced the `loc` and `iloc` accessors for selecting rows and columns from a DataFrame. The `loc` accessor extracts by index label, and the `iloc` accessor extracts by index position. Here's a quick review, using the `df` DataFrame we declared in section 7.4.1:

```
In [42] df
```

```
Out [42]
```

| | x | y |
|---|---|---|
| A | 1 | 2 |
| B | 3 | 4 |

The next example uses `loc` to select the row with an index label of "A":

```
In [43] df.loc["A"]
```

```
Out [43] X    1
          Y    2
          Name: A, dtype: int64
```

The next example uses `iloc` to select the row at index position 1:

```
In [44] df.iloc[1]
```

```
Out [44] X    3
          Y    4
          Name: B, dtype: int64
```

We can use the `loc` and `iloc` accessors to pull rows from a MultiIndex DataFrame. Let's start slow and work our way up.

The neighborhoods DataFrame's MultiIndex has three levels: State, City, and Address. If we know the values to target in each level, we can pass them in a tuple within the square brackets. When we provide a value for a level, we remove the need for the level to exist in the result. The next example provides "TX" for the State level, "Kingchester" for the City level, and "534 Gordon Falls" for the Address level. Pandas returns a Series object with an index constructed from the column headers in neighborhoods:

```
In [45] neighborhoods.loc[("TX", "Kingchester", "534 Gordon Falls")]
```

```
Out [45] Category Subcategory
          Culture Restaurants     C
                      Museums      D+
          Services Police        B
                      Schools      B
          Name: (TX, Kingchester, 534 Gordon Falls), dtype: object
```

If we pass a single label in the square brackets, pandas looks for it in the outermost MultiIndex level. The next example selects the rows with a State value of "CA". State is the first level of the rows' MultiIndex:

```
In [46] neighborhoods.loc["CA"]
```

```
Out [46]
```

| Category | Subcategory | Culture | | Services | |
|----------------|-----------------|-------------|---------|----------|---------|
| | | Restaurants | Museums | Police | Schools |
| City | Street | | | | |
| Dustinmouth | 793 Cynthia ... | A- | A+ | C- | A |
| North Jennifer | 303 Alisha Road | D- | C+ | C+ | A+ |
| Ryanfort | 934 David Run | F | B+ | F | D- |

Pandas returns a DataFrame with a two-level MultiIndex. Notice that the State level is not present. There is no longer a need for it because all three rows belong to that level; there is no longer any variation to display.

Usually, the second argument to the square brackets denotes the column(s) we'd like to extract, but we can also provide the value to look for in the next MultiIndex level. The next example targets rows with a State value of "CA" and a City value of "Dustinmouth". Once again, pandas returns a DataFrame with one fewer level. Because only one level is left, pandas falls back to a plain Index object to store the row labels from the Street level:

```
In [47] neighborhoods.loc["CA", "Dustinmouth"]
```

```
Out [47]
```

| Category | Subcategory | Culture | | Services | |
|--------------------|-------------|-------------|---------|----------|---------|
| | | Restaurants | Museums | Police | Schools |
| Street | | | | | |
| 793 Cynthia Square | | A- | A+ | C- | A |

We can still use the second argument to loc to declare the column(s) to extract. The next example extracts rows with a State value of "CA" in the row MultiIndex and a Category value of "Culture" in the column MultiIndex:

```
In [48] neighborhoods.loc["CA", "Culture"]
```

```
Out [48]
```

| Subcategory | City | Restaurants Museums | |
|----------------|--------------------|---------------------|----|
| | | Street | |
| Dustinmouth | 793 Cynthia Square | A- | A+ |
| North Jennifer | 303 Alisha Road | D- | C+ |
| Ryanfort | 934 David Run | F | B+ |

The syntax in the previous two examples is not ideal because of its ambiguity. The second argument to loc can represent either a value from the second level of the rows' MultiIndex or a value from the first level of the columns' MultiIndex.

The pandas documentation¹ recommends the following indexing strategy to avoid uncertainty. Use the first argument to `loc` for row index labels and the second argument for column index labels. Wrap all arguments for a given index inside a tuple. Following this standard, we should place our row levels' values inside a tuple and our column levels' values inside a tuple as well. The recommended way to access rows with a State value of "CA" and a City value of "Dustinmouth" looks like this:

```
In [49] neighborhoods.loc[("CA", "Dustinmouth")]
```

```
Out [49]
```

| Category | Culture | Services | |
|--------------------|-------------|----------|----------------|
| Subcategory | Restaurants | Museums | Police Schools |
| Street | | | |
| 793 Cynthia Square | A- | A+ | C- |
| | | | A |

This syntax is more straightforward and more consistent; it allows `loc`'s second argument to always represent the columns' index labels to target. The next example pulls out the Services columns for the same state of "CA" and city of "Dustinmouth". We pass "Services" inside a tuple. A one-element tuple requires a comma for Python to recognize it as a tuple:

```
In [50] neighborhoods.loc[("CA", "Dustinmouth"), ("Services",)]
```

```
Out [50]
```

| Subcategory | Police Schools |
|--------------------|----------------|
| Street | |
| 793 Cynthia Square | C- |
| | A |

Here's another helpful hint: pandas distinguishes between list and tuple arguments to accessors. Use a list to store multiple keys. Use a tuple to store the components of one multilevel key.

We can pass a tuple as the second argument to `loc` to provide values for levels in the columns' MultiIndex. The next example targets

- "CA" and "Dustinmouth" in the rows' MultiIndex levels
- "Services" and "Schools" in the columns' MultiIndex levels

The placement of "Services" and "Schools" in a single tuple tells pandas to view them as components that make up a single label. "Services" is the value for the Category level, and "Schools" is the value for the Subcategory level:

```
In [51] neighborhoods.loc[("CA", "Dustinmouth"), ("Services", "Schools")]
```

```
Out [51] Street
        793 Cynthia Square      A
        Name: (Services, Schools), dtype: object
```

¹ See "Advanced indexing with hierarchical index," <http://mng.bz/5WJO>.

What about selecting sequential rows? We can use Python's list-slicing syntax. We place a colon between our starting point and our ending point. The next code sample pulls all consecutive rows with a State value between "NE" and "NH". In pandas slicing, the endpoint (the value after the colon) is inclusive:

```
In [52]: neighborhoods[ "NE" : "NH" ]
```

```
Out [52]
```

| Category | Subcategory | State | City | Culture | | Services | |
|----------|-----------------|-----------------|------|---------------------|----|----------------|----|
| | | | | Restaurants Museums | | Police Schools | |
| | | | | Street | | | |
| NE | Barryborough | 460 Anna Tunnel | | A+ | A+ | B | A |
| | Shawnchester | 802 Cook Cliff | | D- | D+ | D | A |
| | South Kennet... | 346 Wallace ... | | C- | B- | A | A- |
| | South Nathan | 821 Jake Fork | | C+ | D | D+ | A |
| NH | Courtneyfort | 697 Spencer ... | | A+ | A+ | C+ | A+ |
| | East Deborah... | 271 Ryan Mount | | B | C | D+ | B- |
| | Ingramton | 430 Calvin U... | | C+ | D+ | C | C- |
| | North Latoya | 603 Clark Mount | | D- | A- | B+ | B- |
| | South Tara | 559 Michael ... | | C- | C- | F | B |

We can combine list-slicing syntax with tuple arguments. The next example extracts all rows that

- Start from a value of "NE" in the State level and "Shawnchester" in the City level
- End with a value of "NH" in the State level and "North Latoya" in the City level

```
In [53]: neighborhoods.loc[ ( "NE" , "Shawnchester" ) : ( "NH" , "North Latoya" ) ]
```

```
Out [53]
```

| Category | Subcategory | State | City | Culture | | Services | |
|----------|-----------------|-----------------|------|---------------------|----|----------------|----|
| | | | | Restaurants Museums | | Police Schools | |
| | | | | Street | | | |
| NE | Shawnchester | 802 Cook Cliff | | D- | D+ | D | A |
| | South Kennet... | 346 Wallace ... | | C- | B- | A | A- |
| | South Nathan | 821 Jake Fork | | C+ | D | D+ | A |
| | Courtneyfort | 697 Spencer ... | | A+ | A+ | C+ | A+ |
| NH | East Deborah... | 271 Ryan Mount | | B | C | D+ | B- |
| | Ingramton | 430 Calvin U... | | C+ | D+ | C | C- |
| | North Latoya | 603 Clark Mount | | D- | A- | B+ | B- |

Be careful with this syntax; a single missing parenthesis or comma can raise an exception. We can simplify the code by assigning the tuples to descriptive variables and breaking the extraction into smaller pieces. The next example returns the same result set but is significantly easier to read:

```
In [54]: start = ( "NE" , "Shawnchester" )
end = ( "NH" , "North Latoya" )
neighborhoods.loc[start:end]
```

```
Out [54]
```

| Category | | Street | Culture | | Services | |
|-------------|-----------------|-----------------|-------------|---------|----------|---------|
| | | | Restaurants | Museums | Police | Schools |
| Subcategory | State City | | | | | |
| NE | Shawnchester | 802 Cook Cliff | D- | D+ | D | A |
| | South Kennet... | 346 Wallace ... | C- | B- | A | A- |
| | South Nathan | 821 Jake Fork | C+ | D | D+ | A |
| NH | Courtneyfort | 697 Spencer ... | A+ | A+ | C+ | A+ |
| | East Deborah... | 271 Ryan Mount | B | C | D+ | B- |
| | Ingramton | 430 Calvin U... | C+ | D+ | C | C- |
| | North Latoya | 603 Clark Mount | D- | A- | B+ | B- |

We do not have to provide each tuple values for each level. The next example does not include a City-level value for the second tuple:

```
In [55] neighborhoods.loc[("NE", "Shawnchester") : ("NH")]
```

```
Out [55]
```

| Category | | Street | Culture | | Services | |
|-------------|-----------------|-----------------|-------------|---------|----------|---------|
| | | | Restaurants | Museums | Police | Schools |
| Subcategory | State City | | | | | |
| NE | Shawnchester | 802 Cook Cliff | D- | D+ | D | A |
| | South Kennet... | 346 Wallace ... | C- | B- | A | A- |
| | South Nathan | 821 Jake Fork | C+ | D | D+ | A |
| NH | Courtneyfort | 697 Spencer ... | A+ | A+ | C+ | A+ |
| | East Deborah... | 271 Ryan Mount | B | C | D+ | B- |
| | Ingramton | 430 Calvin U... | C+ | D+ | C | C- |
| | North Latoya | 603 Clark Mount | D- | A- | B+ | B- |
| | South Tara | 559 Michael ... | C- | C- | F | B |

Pandas pulls rows starting from ("NE", "Shawnchester") until it reaches the end of all rows with a State value of "NH".

7.4.3 Extracting one or more rows with iloc

The iloc accessor extracts rows and columns by index position. The following examples should be a refresher on concepts covered in chapter 4. We can pass an index position to iloc to extract a single row:

```
In [56] neighborhoods.iloc[25]
```

```
Out [56] Category Subcategory
      Culture Restaurants A+
                  Museums   A
      Services Police    A+
                  Schools  C+
Name: (CT, East Jessicaland, 208 Todd Knolls), dtype: object
```

We can pass two arguments to iloc to represent the row and column indices. The next example targets the row with index position 25 and the column with index position 2:

```
In [57] neighborhoods.iloc[25, 2]
```

```
Out [57] 'A+'
```

We can pull out multiple rows by wrapping their index positions in a list:

```
In [58] neighborhoods.iloc[[25, 30]]
```

```
Out [58]
```

| Category | Subcategory | State | City | Street | Culture | | Services | |
|----------|-----------------|-------|-------------|--------|---------------------|----|----------------|----|
| | | | | | Restaurants Museums | | Police Schools | |
| | | | | | A+ | A | A+ | C+ |
| CT | East Jessica... | 208 | Todd Knolls | | A+ | A | A+ | C+ |
| DC | East Lisaview | 910 | Sandy Ramp | | A- | A+ | B | B |

There's a big difference between `loc` and `iloc` when it comes to slicing. When we're index slicing with `iloc`, the endpoint is exclusive. In the preceding example, the record with a street of "910 Sandy Ramp" has index position 30. When we provide 30 as the `iloc` endpoint in the next example, pandas pulls up to that index but does not include it:

```
In [59] neighborhoods.iloc[25:30]
```

```
Out [59]
```

| Category | Subcategory | State | City | Street | Culture | | Services | |
|----------|-----------------|-------|-------------|--------|---------------------|----|----------------|----|
| | | | | | Restaurants Museums | | Police Schools | |
| | | | | | A+ | A | A+ | C+ |
| CT | East Jessica... | 208 | Todd Knolls | | A+ | A | A+ | C+ |
| | New Adrianhaven | 048 | Brian Cove | | A- | C+ | A+ | D- |
| | Port Mike | 410 | Keith Lodge | | D- | A | B+ | D |
| | Sethstad | 139 | Bailey G... | | C | C- | C+ | A+ |
| DC | East Jessica | 149 | Norman C... | | A- | C- | C+ | A- |

Column slicing follows the same principles. The next example pulls the columns from index positions 1 to 3 (exclusive):

```
In [60] neighborhoods.iloc[25:30, 1:3]
```

```
Out [60]
```

| Category | Subcategory | State | City | Street | Culture Services | |
|----------|-----------------|-------|-------------|--------|------------------|----|
| | | | | | Museums Police | |
| | | | | | A | A+ |
| CT | East Jessica... | 208 | Todd Knolls | | A | A+ |
| | New Adrianhaven | 048 | Brian Cove | | C+ | A+ |
| | Port Mike | 410 | Keith Lodge | | A | B+ |
| | Sethstad | 139 | Bailey G... | | C- | C+ |
| DC | East Jessica | 149 | Norman C... | | C- | C+ |

Pandas also permits negative slices. The next example pulls rows starting from the fourth-to-last row and the columns starting from the second-to-last column:

```
In [61] neighborhoods.iloc[-4:, -2:]
```

```
Out [61]
```

| Category | | Services | | | |
|-------------|-------------|-----------------|----|----|--|
| Subcategory | | Police Schools | | | |
| State | City | Street | | | |
| WY | Lake Nicole | 933 Jennifer... | A- | C | |
| | Martintown | 013 Bell Mills | A- | B- | |
| | Port Jason | 624 Faulkner... | C+ | C+ | |
| | Reneeshire | 717 Patel Sq... | D | A | |

Pandas assigns each DataFrame row an index position, not each value in a given index level. Thus, we cannot index across consecutive MultiIndex levels with `iloc`. This limitation is an intentional design decision by the pandas development team. As developer Jeff Reback states, `iloc` serves as a “strict positional indexer” that “does not regard the structure [of the DataFrame] at all.”²

7.5 Cross-sections

The `xs` method allows us to extract rows by providing a value for *one* MultiIndex level. We pass the method a `key` parameter with the value to look for. We pass the `level` parameter either the numeric position or the name of the index level in which to look for the value. For example, let’s say we wanted to find all addresses in a city of Lake Nicole, regardless of the state or street. City is the second level in the MultiIndex; it has an index position of 1 in the level hierarchy:

```
In [62] # The two lines below are equivalent
neighborhoods.xs(key = "Lake Nicole", level = 1)
neighborhoods.xs(key = "Lake Nicole", level = "City")
```

Out [62]

| Category | | Culture | | Services | |
|-------------|---------------------|-------------|---------|----------|---------|
| Subcategory | | Restaurants | Museums | Police | Schools |
| State | Street | | | | |
| OR | 650 Angela Track | D | C- | D | F |
| WY | 754 Weaver Turnpike | B | D- | B | D |
| | 933 Jennifer Burg | C | A+ | A- | C |

There are three addresses in a city of "Lake Nicole" across two states. Notice that pandas removes the City level from the new DataFrame’s MultiIndex. The City value is fixed ("Lake Nicole"), so there is no need for pandas to include it.

We can apply the same extraction techniques to columns by passing the `axis` parameter an argument of "columns". The next example selects the columns with a key of "Museums" in the Subcategory level of the column MultiIndex. Only one column fits that description:

```
In [63] neighborhoods.xs(
    axis = "columns", key = "Museums", level = "Subcategory"
).head()
```

Out [63]

² See Jeff Reback, “Inconsistent behavior of loc and iloc for MultiIndex,” <https://github.com/pandas-dev/pandas/issues/15228>.

| Category | | Culture | | | |
|----------|----------------|---------------------|----|--|--|
| State | City | Street | | | |
| AK | Rowlandchester | 386 Rebecca Cove | A- | | |
| | Scottstad | 082 Leblanc Freeway | C- | | |
| | | 114 Jones Garden | D- | | |
| | Stevenshire | 238 Andrew Rue | A | | |
| AL | Clarkland | 430 Douglas Mission | F | | |

Notice that the Subcategory level is not present in the returned DataFrame, but the Category level is still present. Pandas includes it because there is still potential for variation (such as multiple values) in the Category level. When we pull out values from an intermediate level, they can belong to multiple top-level labels.

We can also provide the `xs` method with keys across nonconsecutive MultiIndex levels. We pass them in a tuple. Suppose that we want the rows with a Street value of "238 Andrew Rue" and a State of "AK", irrespective of the City value. That's not a problem with `xs`:

```
In [64] # The two lines below are equivalent
neighborhoods.xs(
    key = ("AK", "238 Andrew Rue"), level = ["State", "Street"]
)

neighborhoods.xs(
    key = ("AK", "238 Andrew Rue"), level = [0, 2]
)

Out [64]

Category      Culture      Services
Subcategory Restaurants Museums   Police Schools
City
Stevenshire        D-          A       A-       A-
```

The ability to target values in only one level is a powerful feature of MultiIndexes.

7.6 Manipulating the Index

At the start of the chapter, we contorted our neighborhoods data set into its current shape by altering the parameters to the `read_csv` function. Pandas also allows us to manipulate the index on an existing DataFrame. Let's take a look.

7.6.1 Resetting the index

The neighborhoods DataFrame currently has State as its outermost MultiIndex level, followed by City and Street:

```
In [65] neighborhoods.head()

Out [65]

Category      Culture      Services
Subcategory Restaurants Museums   Police Schools
State City      Street
AK   Rowlandchester 386 Rebecca Cove      C-       A-       A+       C
     Scottstad      082 Leblanc Fr...      D         C-       D       B+
                           114 Jones Garden      D-       D-       D       D
```

| | | | | | | |
|----|-------------|-------------------|----|---|----|----|
| | Stevenshire | 238 Andrew Rue | D- | A | A- | A- |
| AL | Clarkland | 430 Douglas Mi... | A | F | C+ | B+ |

The `reorder_levels` method arranges the MultiIndex levels in a specified order. We pass its `order` parameter a list of levels in a desired order. The next example swaps the positions of the City and State levels:

```
In [66] new_order = ["City", "State", "Street"]
neighborhoods.reorder_levels(order = new_order).head()
```

```
Out [66]
```

| Category | Subcategory | City | Culture | | | Services | |
|----------------|-------------|-----------------|---------|--|-------------|----------|----------------|
| | | | State | | Restaurants | Museums | Police Schools |
| | | | Street | | | | |
| Rowlandchester | AK | 386 Rebecca ... | | | C- | A- | A+ C |
| Scottstad | AK | 082 Leblanc ... | | | D | C- | D B+ |
| | | 114 Jones Ga... | | | D- | D- | D D |
| Stevenshire | AK | 238 Andrew Rue | | | D- | A | A- A- |
| Clarkland | AL | 430 Douglas ... | | | A | F | C+ B+ |

We can also pass the `order` parameter a list of integers. The numbers must represent the current index positions of the MultiIndex levels. If we want State to be the first level in the new MultiIndex, for example, we have to start the list with 1—the State level's index position in the current MultiIndex. The next code sample returns the same result as the preceding one:

```
In [67] neighborhoods.reorder_levels(order = [1, 0, 2]).head()
```

```
Out [67]
```

| Category | Subcategory | City | Culture | | | Services | |
|----------------|-------------|-----------------|---------|--|-------------|----------|----------------|
| | | | State | | Restaurants | Museums | Police Schools |
| | | | Street | | | | |
| Rowlandchester | AK | 386 Rebecca ... | | | C- | A- | A+ C |
| Scottstad | AK | 082 Leblanc ... | | | D | C- | D B+ |
| | | 114 Jones Ga... | | | D- | D- | D D |
| Stevenshire | AK | 238 Andrew Rue | | | D- | A | A- A- |
| Clarkland | AL | 430 Douglas ... | | | A | F | C+ B+ |

What if we want to get rid of the index? Perhaps we want to set a different combination of columns as the index labels. The `reset_index` method returns a new DataFrame that integrates the former MultiIndex levels as columns. Pandas replaces the former MultiIndex with its standard numeric one:

```
In [68] neighborhoods.reset_index().tail()
```

```
Out [68]
```

| Category | State | City | Street | Culture | | Services | |
|----------|-------|---------|---------|-------------|---------|----------|---------|
| | | | | Restaurants | Museums | Police | Schools |
| 246 | WY | Lake... | 754 ... | B | D- | B | D |
| 247 | WY | Lake... | 933 ... | C | A+ | A- | C |
| 248 | WY | Mart... | 013 ... | C- | D | A- | B- |

| | | | | | | | | |
|-----|----|---------|-----|-----|----|----|----|----|
| 249 | WY | Port... | 624 | ... | A- | F | C+ | C+ |
| 250 | WY | Rene... | 717 | ... | B | B+ | D | A |

Notice that the three new columns (State, City, and Street) become values in Category, the outermost level of the columns' MultiIndex. To ensure consistency among columns (making each one a tuple of two values), pandas assigns the three new columns a Subcategory value of an empty string.

We can add the three columns to an alternate MultiIndex level. Pass the desired level's index position or name to the `reset_index` method's `col_level` parameter. The next example integrates the State, City, and Street columns into the Subcategory level of the columns' MultiIndex:

```
In [69] # The two lines below are equivalent
neighborhoods.reset_index(col_level = 1).tail()
neighborhoods.reset_index(col_level = "Subcategory").tail()
```

Out [69]

| Category | Culture | | | | | Services | | |
|----------|-------------|-------|---------|--------|-------------|----------|--------|---------|
| | Subcategory | State | City | Street | Restaurants | Museums | Police | Schools |
| 246 | | WY | Lake... | 754 | ... | B | D- | B |
| 247 | | WY | Lake... | 933 | ... | C | A+ | A- |
| 248 | | WY | Mart... | 013 | ... | C- | D | A- |
| 249 | | WY | Port... | 624 | ... | A- | F | C+ |
| 250 | | WY | Rene... | 717 | ... | B | B+ | D |

Now pandas will default to an empty string for Category, the parent level that holds the Subcategory level under which State, City, and Street fall. We can replace the empty string with a value of our choice by passing an argument to the `col_fill` parameter. In the next example, we group the three new columns under an Address parent level. Now the outer Category level holds the three distinct values Address, Culture, and Services:

```
In [70] neighborhoods.reset_index(
    col_fill = "Address", col_level = "Subcategory"
).tail()
```

Out [70]

| Category | Culture | | | | | Services | | | |
|----------|---------|-------------|-------|---------|--------|-------------|---------|--------|---------|
| | Address | Subcategory | State | City | Street | Restaurants | Museums | Police | Schools |
| 246 | | | WY | Lake... | 754 | ... | B | D- | B |
| 247 | | | WY | Lake... | 933 | ... | C | A+ | A- |
| 248 | | | WY | Mart... | 013 | ... | C- | D | A- |
| 249 | | | WY | Port... | 624 | ... | A- | F | C+ |
| 250 | | | WY | Rene... | 717 | ... | B | B+ | D |

The standard invocation of `reset_index` transforms all index levels into regular columns. We can also move a single index level by passing its name to the `levels` parameter. The next example moves the Street level from the MultiIndex to a regular DataFrame column:

```
In [71] neighborhoods.reset_index(level = "Street").tail()

Out [71]
```

| Category | Subcategory | State | Street | Culture | Services | | |
|----------|-------------|-------------------|-------------|---------|----------|---------|----|
| | | | Restaurants | Museums | Police | Schools | |
| | | | City | | | | |
| WY | Lake Nicole | 754 Weaver Tur... | | B | D- | B | D |
| | Lake Nicole | 933 Jennifer Burg | | C | A+ | A- | C |
| | Martintown | 013 Bell Mills | | C- | D | A- | B- |
| | Port Jason | 624 Faulkner O... | | A- | F | C+ | C+ |
| | Reneeshire | 717 Patel Square | | B | B+ | D | A |

We can move multiple index levels by passing them in a list:

```
In [72] neighborhoods.reset_index(level = ["Street", "City"]).tail()

Out [72]
```

| Category | Subcategory | State | City | Street | Culture | Services | |
|----------|-------------|-------------|-------------|---------|---------|----------|----|
| | | | Restaurants | Museums | Police | Schools | |
| | | | | | | | |
| WY | Lake Nicole | 754 Weav... | | B | D- | B | D |
| WY | Lake Nicole | 933 Jenn... | | C | A+ | A- | C |
| WY | Martintown | 013 Bell... | | C- | D | A- | B- |
| WY | Port Jason | 624 Faul... | | A- | F | C+ | C+ |
| WY | Reneeshire | 717 Pate... | | B | B+ | D | A |

What about removing a level from the MultiIndex? If we pass the `reset_index` method's `drop` parameter a value of `True`, pandas will delete the specified level instead of adding it to the columns. The next `reset_index` example removes the Street level:

```
In [73] neighborhoods.reset_index(level = "Street", drop = True).tail()

Out [73]
```

| Category | Subcategory | State | Culture | | Services | |
|----------|-------------|-------|-------------|---------|----------|---------|
| | | | Restaurants | Museums | Police | Schools |
| | | | City | | | |
| WY | Lake Nicole | | B | D- | B | D |
| | Lake Nicole | | C | A+ | A- | C |
| | Martintown | | C- | D | A- | B- |
| | Port Jason | | A- | F | C+ | C+ |
| | Reneeshire | | B | B+ | D | A |

To set ourselves up for section 7.6.2, let's make our index reset permanent by overwriting the `neighborhoods` variable with the new DataFrame. This operation moves all three index levels to columns in the DataFrame:

```
In [74] neighborhoods = neighborhoods.reset_index()
```

Now we have seven columns in neighborhoods with a MultiIndex on only the column axis.

7.6.2 Setting the index

Let's check in on our DataFrame to jog our memory:

```
In [75]: neighborhoods.head(3)
```

```
Out [75]
```

| Category | State | City | Street | Culture | | Services | |
|----------|-------|---------|---------|-------------|---------|----------|---------|
| | | | | Restaurants | Museums | Police | Schools |
| 0 | AK | Rowl... | 386 ... | C- | A- | A+ | C |
| 1 | AK | Scot... | 082 ... | D | C- | D | B+ |
| 2 | AK | Scot... | 114 ... | D- | D- | D | D |

The `set_index` method sets one or more DataFrame columns as the new index. We can pass the column(s) to use to its `keys` parameter:

```
In [76]: neighborhoods.set_index(keys = "City").head()
```

```
Out [76]
```

| Category | State | Street | Culture | | Services | |
|----------------|-------|----------------|-------------|---------|----------|---------|
| | | | Restaurants | Museums | Police | Schools |
| City | | | | | | |
| Rowlandchester | AK | 386 Rebecca... | C- | A- | A+ | C |
| Scottstad | AK | 082 Leblanc... | D | C- | D | B+ |
| Scottstad | AK | 114 Jones G... | D- | D- | D | D |
| Stevenshire | AK | 238 Andrew Rue | D- | A | A- | A- |
| Clarkland | AL | 430 Douglas... | A | F | C+ | B+ |

What if we want one of the last four columns to serve as the index?. The next example passes the `keys` parameter a tuple with the values to target at each MultiIndex level:

```
In [77]: neighborhoods.set_index(keys = ("Culture", "Museums")).head()
```

```
Out [77]
```

| Category | State | City | Street | Culture Services | |
|--------------------|-------|-----------|-----------|------------------|----------------|
| | | | | Restaurants | Police Schools |
| (Cultur...) | | | | | |
| A- | AK | Rowlan... | 386 Re... | C- | A+ C |
| C- | AK | Scottstad | 082 Le... | D | D B+ |
| D- | AK | Scottstad | 114 Jo... | D- | D D |
| A | AK | Steven... | 238 An... | D- | A- A- |
| F | AL | Clarkland | 430 Do... | A | C+ B+ |

To create a MultiIndex on the row axis, we can pass a list with multiple columns to the `keys` parameter:

```
In [78]: neighborhoods.set_index(keys = ["State", "City"]).head()
```

```
Out [78]
```

| Category | | Street | Culture | | Services | | | |
|----------|----------------|--------|-------------|-------------|----------|----------------|----|----|
| | | | Subcategory | Restaurants | Museums | Police Schools | | |
| State | | | City | | | | | |
| AK | Rowlandchester | 386 | Rebecca... | | C- | A- | A+ | C |
| | Scottstad | 082 | Leblanc... | | D | C- | D | B+ |
| | Scottstad | 114 | Jones G... | | D- | D- | D | D |
| | Stevenshire | 238 | Andrew Rue | | D- | A | A- | A- |
| AL | Clarkland | 430 | Douglas... | | A | F | C+ | B+ |

As we've seen frequently in pandas, there are many permutations and combinations for shaping a data set for analysis. When defining a DataFrame's indices, ask yourself which values matter most to your current problem. What is the key piece of information? Are several pieces of data intrinsically tied together? Which data points would you like to store as rows versus columns? Do rows or columns comprise a group or category? For many of these problems, a MultiIndex can provide an effective solution for storing your data.

7.7 Coding challenge

Here's your chance to practice the concepts introduced in this chapter.

7.7.1 Problems

The investments.csv data set holds more than 27,000 records of startup investments gathered from the website Crunchbase. Each startup has a Name, a Market, a Status, a State of operation, and a number of Funding Rounds:

```
In [79] investments = pd.read_csv("investments.csv")
investments.head()
```

```
Out [79]
```

| | Name | Market | Status | State | Funding | Rounds |
|---|--------------------|----------|-----------|-------|---------|--------|
| 0 | #waywire | News | Acquired | NY | | 1 |
| 1 | &TV Communications | Games | Operating | CA | | 2 |
| 2 | -R- Ranch and Mine | Tourism | Operating | TX | | 2 |
| 3 | 004 Technologies | Software | Operating | IL | | 1 |
| 4 | 1-4 All | Software | Operating | NC | | 1 |

Let's add a MultiIndex to this DataFrame. We can begin by identifying the number of unique values in each column with the nunique method. Columns with a small number of unique items usually represent categorical data and are good candidates for index levels:

```
In [80] investments.nunique()
```

```
Out [80] Name          27763
Market         693
Status          3
State           61
Funding Rounds  16
dtype: int64
```

Let's create a three-level MultiIndex with the Status, Funding Rounds, and State columns. We'll order the columns so that the ones with the smallest number of values come first. The fewer unique values in a level, the quicker pandas can extract its rows. We'll also sort the DataFrame index to accelerate lookup time:

```
In [81] investments = investments.set_index(
    keys = ["Status", "Funding Rounds", "State"]
).sort_index()
```

Here's what investments currently looks like:

```
In [82] investments.head()
```

```
Out [82]
```

| Status | Funding Rounds | State | Name | Market |
|----------|----------------|-------|---------------------|---------------------|
| Acquired | 1 | AB | Hallpass Media | Games |
| | | AL | EnteGreat | Enterprise Software |
| | | AL | Onward Behaviora... | Biotechnology |
| | | AL | Proxsys | Biotechnology |
| | | AZ | Envox Group | Public Relations |

Here are the challenges for this section:

- 1 Extract all rows with a Status of "Closed".
- 2 Extract all rows with a Status of "Acquired" and 10 funding rounds.
- 3 Extract all rows with a Status of "Operating", six funding rounds, and a State of "NJ".
- 4 Extract all rows with a Status of "Closed" and eight funding rounds. Pull out only the Name column.
- 5 Extract all rows with a State of "NJ", irrespective of the values in the Status and Funding Rounds levels.
- 6 Reincorporate the MultiIndex levels back into the DataFrame as columns.

7.7.2 Solutions

Let's tackle the problems one by one:

- 1 To extract all rows with a Status of "Closed", we can use the `loc` accessor. We'll pass a tuple with a single value of "Closed". Remember that a one-element tuple requires a comma:

```
In [83] investments.loc[("Closed",)].head()
```

```
Out [83]
```

| Funding Rounds | State | Name | Market |
|----------------|-------|-----------------------------|----------------------|
| 1 | AB | Cardinal Media Technologies | Social Network Media |
| | AB | Easy Bill Online | Tracking |
| | AB | Globel Direct | Public Relations |
| | AB | Ph03nix New Media | Games |
| | AL | Naubo | News |

- 2 Next, we need to pull out rows that fit two conditions: a Status value of "Acquired" and a Funding Rounds value of 10. These are sequential levels in the MultiIndex. We can pass a tuple with the proper values to the loc accessor:

```
In [84] investments.loc[("Acquired", 10)]  
Out [84]
```

| State | | Name | Market |
|--------------|------------------|-------------|---------------|
| NY | Genesis Networks | Web Hosting | |
| TX | ACTIVE Network | Software | |

- 3 We can use the same solution that we used for the preceding two problems. This time around, we need to provide a tuple of three values, one for each MultiIndex level:

```
In [85] investments.loc[("Operating", 6, "NJ")]  
Out [85]
```

| Status | Funding Rounds | State | Name | Market |
|---------------|-----------------------|--------------|--------------------|-------------------|
| Operating | 6 | NJ | Agile Therapeutics | Biotechnology |
| | | NJ | Agilence | Retail Technology |
| | | NJ | Edge Therapeutics | Biotechnology |
| | | NJ | Nistica | Web Hosting |

- 4 To extract DataFrame columns, we can pass a second argument to the loc accessor. For this problem, we'll pass a one-element tuple with the Name column. The first argument still holds the values for the Status and Funding Rounds levels:

```
In [86] investments.loc[("Closed", 8), ("Name",)]  
Out [86]
```

| State | Name |
|--------------|---------------------|
| CA | CipherMax |
| CA | Dilithium Networks |
| CA | Moblyng |
| CA | SolFocus |
| CA | Solyndra |
| FL | Extreme Enterprises |
| GA | MedShape |
| NC | Biolex Therapeutics |
| WA | Cozi Group |

- 5 The next challenge asks us to extract rows with a value of "NJ" in the State level. We can use the xs method, passing either the level's index position or the level's name to the level parameter:

```
In [87] # The two lines below are equivalent
investments.xs(key = "NJ", level = 2).head()
investments.xs(key = "NJ", level = "State").head()

Out [87]
```

| Status | Funding Rounds | Name | | Market |
|----------|----------------|-----------------|---------------------|---------------|
| | | | | |
| Acquired | 1 | AkaRx | | Biotechnology |
| | 1 | Aptalis Pharma | | Biotechnology |
| | 1 | Cadent | | Software |
| | 1 | Cancer Genetics | Health And Wellness | |
| | 1 | Clacendix | | E-Commerce |

- 6 Finally, we want to add the MultiIndex levels back to the DataFrame as columns. We'll invoke the `reset_index` method to reincorporate the index levels and overwrite the `investments` DataFrame to make the change permanent:

```
In [88] investments = investments.reset_index()
investments.head()
```

Out [88]

| Status | Funding Rounds | State | Name | | Market |
|--------|----------------|-------|------|-------------------------------|------------------|
| | | | | | |
| 0 | Acquired | 1 | AB | Hallpass Media | Games |
| 1 | Acquired | 1 | AL | EnteGreat Enterprise Software | Software |
| 2 | Acquired | 1 | AL | Onward Behaviora... | Biotechnology |
| 3 | Acquired | 1 | AL | Proxsys | Biotechnology |
| 4 | Acquired | 1 | AZ | Envox Group | Public Relations |

Congratulations on completing the coding challenge!

Summary

- A MultiIndex is an index made of multiple levels.
- A MultiIndex uses tuples of values to store its labels.
- A DataFrame can store a MultiIndex on both its row and column axis.
- The `sort_index` method sorts MultiIndex levels. Pandas can sort index levels individually or as a group.
- The label-based `loc` and the position-based `iloc` accessors require additional arguments to extract the proper combination of rows and columns.
- Pass tuples to the `loc` and `iloc` accessors to avoid ambiguity.
- The `reset_index` method integrates index levels as DataFrame columns.
- Pass the `set_index` method a list of columns to build a MultiIndex from existing DataFrame columns.

Reshaping and pivoting



This chapter covers

- Comparing wide and narrow data
- Generating a pivot table from a `DataFrame`
- Aggregating values by sum, average, count, and more
- Stacking and unstacking `DataFrame` index levels
- Melting a `DataFrame`

A data set can arrive in a format unsuited for the analysis that we'd like to perform on it. Sometimes, issues are confined to a specific column, row, or cell. A column may have the wrong data type, a row may have missing values, or a cell may have incorrect character casing. At other times, a data set may have larger structural problems that extend beyond the data. Perhaps the data set stores its values in a format that makes it easy to extract a single row but difficult to aggregate the data.

Reshaping a data set means manipulating it into a different shape, one that tells a story that could not be gleaned from its original presentation. Reshaping offers a

new view or perspective on the data. This skill is critical; one study estimates that 80% of data analysis consists of cleaning up data and contorting it into the proper shape.¹

In this chapter, we'll explore new pandas techniques for molding data sets into the shapes we desire. First, we'll look at how to summarize a larger data set in a concise pivot table. Then we'll proceed in the opposite direction, learning how to split an aggregated data set. By the end, you'll be a master of contorting data into whatever presentation best fits your analysis.

8.1 Wide vs. narrow data

Before we dive into more methods, let's talk briefly about data set structure. A data set can store its values in wide or narrow format. A *narrow* data set is also called a *long* or a *tall* data set. These names reflect the direction in which the data set expands as we add more values to it. A *wide* data set increases in width; it grows out. A narrow/long/tall data set increases in height; it grows down.

Take a peek at the following table, which measures temperatures in two cities over two days:

| Weekday | Miami | New York |
|---------|---------|----------|
| 0 | Monday | 100 |
| 1 | Tuesday | 105 |

Consider the *variables*, the measurements that vary. One might think that the only variables in this data set are the weekdays and the temperatures. But an additional variable is hiding in the column names: the city. This data set stores the same variable—temperature—across two columns instead of one. The Miami and New York headers do not describe the data their columns store—that is, 100 is not a type of Miami in the same way that Monday is a type of Weekday. The data set has hidden the varying cities variable by storing it in the column headers. We can categorize this table as being a wide data set. A wide data set expands horizontally.

Suppose that we introduced temperature measurements for two more cities. We would have to add two new columns for the same variable: the temperature. Notice the direction in which the data set expands. The data grows wider, not taller:

| Weekday | Miami | New York | Chicago | San Francisco |
|---------|---------|----------|---------|---------------|
| 0 | Monday | 100 | 65 | 50 |
| 1 | Tuesday | 105 | 70 | 58 |

Is horizontal expansion a bad thing? Not necessarily. A wide data set is ideal for seeing the aggregate picture—the complete story. If what we care about is the temperatures on Monday and Tuesday, the data set is easy to read and understand. But the wide format has its share of disadvantages too. The data set becomes more difficult to work with as we add more columns. Suppose that we wrote code to calculate the average temperature across all days. Now the temperatures are stored across four columns. If

¹ See Hadley Wickham, “Tidy Data,” *Journal of Statistical Software*, <https://vita.had.co.nz/papers/tidy-data.pdf>.

we added another city column, we'd have to alter our calculation logic to include it. The design is less flexible.

A narrow data set grows vertically. A narrow format makes it easier to manipulate existing data and to add new records. Each variable is isolated to a single column. Compare the first table in this section with the following table:

| Weekday | City | Temperature |
|---------|---------|-------------|
| 0 | Monday | Miami |
| 1 | Monday | New York |
| 2 | Tuesday | Miami |
| 3 | Tuesday | New York |

To include temperatures for two more cities, we would add rows instead of columns. The data grows taller, not wider:

| Weekday | City | Temperature |
|---------|---------|---------------|
| 0 | Monday | Miami |
| 1 | Monday | New York |
| 2 | Monday | Chicago |
| 3 | Monday | San Francisco |
| 4 | Tuesday | Miami |
| 5 | Tuesday | New York |
| 6 | Tuesday | Chicago |
| 7 | Tuesday | San Francisco |

Is it easier to locate the temperatures for cities on Monday? I would argue no because now the data is scattered across four rows. But it is easier to calculate the average temperature because we have isolated the temperature values to a single column. As we add more rows, the average calculation logic remains the same.

The optimal storage format for a data set depends on the insight we're trying to glean from it. Pandas offers tools to transform `DataFrames` from narrow formats to wide formats and vice versa. We'll learn how to apply both transformations throughout the rest of the chapter.

8.2 *Creating a pivot table from a DataFrame*

Our first data set, `sales_by_employee.csv`, is a list of business deals at a fictional company. Each row includes the sale's Date, the salesman's Name, the Customer, and the Revenue and Expenses from the deal:

```
In [1] import pandas as pd
In [2] pd.read_csv("sales_by_employee.csv").head()
Out [2]
```

| | Date | Name | Customer | Revenue | Expenses |
|---|--------|-------|---------------|---------|----------|
| 0 | 1/1/20 | Oscar | Logistics XYZ | 5250 | 531 |
| 1 | 1/1/20 | Oscar | Money Corp. | 4406 | 661 |
| 2 | 1/2/20 | Oscar | PaperMaven | 8661 | 1401 |
| 3 | 1/3/20 | Oscar | PaperGenius | 7075 | 906 |
| 4 | 1/4/20 | Oscar | Paper Pound | 2524 | 1767 |

For utility's sake, let's convert the strings in the Date column to datetime objects with the `read_csv` function's `parse_dates` parameter. After that change, this import looks good to go. We can assign the DataFrame to a `sales` variable:

```
In [3] sales = pd.read_csv(
    "sales_by_employee.csv", parse_dates = ["Date"]
)

sales.tail()

Out [3]
```

| Date | Name | Customer | Revenue | Expenses |
|---------------|-------|-------------------|---------|----------|
| 21 2020-01-01 | Creed | Money Corp. | 4430 | 548 |
| 22 2020-01-02 | Creed | Average Paper Co. | 8026 | 1906 |
| 23 2020-01-02 | Creed | Average Paper Co. | 5188 | 1768 |
| 24 2020-01-04 | Creed | PaperMaven | 3144 | 1314 |
| 25 2020-01-05 | Creed | Money Corp. | 938 | 1053 |

With our data set loaded, let's explore how we can aggregate its data with a pivot table.

8.2.1 *The pivot_table method*

A *pivot table* aggregates a column's values and groups the results by using other columns' values. The word *aggregate* describes a summary computation that involves multiple values. Example aggregations include average, sum, median, and count. A pivot table in pandas is similar to the Pivot Table feature in Microsoft Excel.

As always, an example proves to be most helpful, so let's tackle our first challenge. Multiple salesmen closed deals on the same date. In addition, the same salesmen closed multiple deals on the same date. What if we want to sum the revenue by date and see how much each salesman contributed to the daily totals?

We follow four steps to create a pivot table:

- 1 Select the column(s) whose values we want to aggregate.
- 2 Choose the aggregation operation to apply to the column(s).
- 3 Select the column(s) whose values will group the aggregated data into categories.
- 4 Determine whether to place the groups on the row axis, the column axis, or both axes.

Let's proceed one step at a time. First, we'll need to invoke the `pivot_table` method on our existing `sales` DataFrame. The method's `index` parameter accepts the column whose values will make up the pivot table's index labels. Pandas will use the unique values from that column to group the results.

The next example uses the Date column's values for the index labels of the pivot table. The Date column contains five unique dates. Pandas applies its default aggregation operation, an average, to all numeric columns in `sales` (Expenses and Revenue):

```
In [4] sales.pivot_table(index = "Date")
```

```
Out [4]
```

| Date | Expenses | Revenue |
|------------|-------------|-------------|
| 2020-01-01 | 637.500000 | 4293.500000 |
| 2020-01-02 | 1244.400000 | 7303.000000 |
| 2020-01-03 | 1313.666667 | 4865.833333 |
| 2020-01-04 | 1450.600000 | 3948.000000 |
| 2020-01-05 | 1196.250000 | 4834.750000 |

The method returns a regular DataFrame object. It may be a bit underwhelming, but this DataFrame is a pivot table! The table shows average expenses and average revenue organized by the five unique dates in the Date column.

We declare the aggregation function with the aggfunc parameter; its default argument is "mean". The following code produces the same result as the preceding code:

```
In [5] sales.pivot_table(index = "Date", aggfunc = "mean")
```

```
Out [5]
```

| Date | Expenses | Revenue |
|------------|-------------|-------------|
| 2020-01-01 | 637.500000 | 4293.500000 |
| 2020-01-02 | 1244.400000 | 7303.000000 |
| 2020-01-03 | 1313.666667 | 4865.833333 |
| 2020-01-04 | 1450.600000 | 3948.000000 |
| 2020-01-05 | 1196.250000 | 4834.750000 |

We'll have to modify some method arguments to reach our original goal: a sum of each date's revenue organized by salesman. First, let's swap the aggfunc parameter's argument to "sum" to add the values in Expenses and Revenue:

```
In [6] sales.pivot_table(index = "Date", aggfunc = "sum")
```

```
Out [6]
```

| Date | Expenses | Revenue |
|------------|----------|---------|
| 2020-01-01 | 3825 | 25761 |
| 2020-01-02 | 6222 | 36515 |
| 2020-01-03 | 7882 | 29195 |
| 2020-01-04 | 7253 | 19740 |
| 2020-01-05 | 4785 | 19339 |

For now, we care only about summing the values in the Revenue column. The values parameter accepts the DataFrame column(s) that pandas will aggregate. To aggregate only one column's values, we can pass the parameter a string with the column name:

```
In [7] sales.pivot_table(
        index = "Date", values = "Revenue", aggfunc = "sum"
    )
```

```
Out [7]
```

| Date | Revenue |
|------------|---------|
| 2020-01-01 | 25761 |
| 2020-01-02 | 36515 |
| 2020-01-03 | 29195 |
| 2020-01-04 | 19740 |
| 2020-01-05 | 19339 |

To aggregate values across multiple columns, we can pass values a list of columns.

We have a sum of revenue grouped by date. Our final step is communicating how much each salesman contributed to the daily total. One presentational view that seems to be optimal is placing each salesman's name in a separate column. In other words, we'd like to use the Name column's unique values as the column headers in the pivot table. Let's add a columns parameter to the method invocation and pass it an argument of "Name":

```
In [8] sales.pivot_table(
    index = "Date",
    columns = "Name",
    values = "Revenue",
    aggfunc = "sum"
)
```

```
Out [8]
```

| Name | Creed | Dwight | Jim | Michael | Oscar |
|------------|---------|---------|--------|---------|--------|
| Date | | | | | |
| 2020-01-01 | 4430.0 | 2639.0 | 1864.0 | 7172.0 | 9656.0 |
| 2020-01-02 | 13214.0 | NaN | 8278.0 | 6362.0 | 8661.0 |
| 2020-01-03 | NaN | 11912.0 | 4226.0 | 5982.0 | 7075.0 |
| 2020-01-04 | 3144.0 | NaN | 6155.0 | 7917.0 | 2524.0 |
| 2020-01-05 | 938.0 | 7771.0 | NaN | 7837.0 | 2793.0 |

That's it! We have an aggregated sum of revenue organized by dates on the row axis and salesmen on the column axis. Notice the presence of NaNs in the data set. A NaN denotes that the salesman did not have a row in sales with a Revenue value for a given date. Dwight does not have any sales row with a Date value of 2020-01-02, for example. The pivot table needs the index label of 2020-01-02 to exist for the four salesmen who have a revenue value for that date. Pandas plugs in the missing holes with NaNs. The presence of NaN values also forces the coercion of integers into floating-point numbers.

We can use the fill_value parameter to replace all pivot table NaNs with a fixed value. Let's fill in the data gaps with zeroes:

```
In [9] sales.pivot_table(
    index = "Date",
    columns = "Name",
    values = "Revenue",
    aggfunc = "sum",
    fill_value = 0
)
```

```
Out [9]
```

| Name | Creed | Dwight | Jim | Michael | Oscar |
|------------|-------|--------|------|---------|-------|
| Date | | | | | |
| 2020-01-01 | 4430 | 2639 | 1864 | 7172 | 9656 |
| 2020-01-02 | 13214 | 0 | 8278 | 6362 | 8661 |
| 2020-01-03 | 0 | 11912 | 4226 | 5982 | 7075 |
| 2020-01-04 | 3144 | 0 | 6155 | 7917 | 2524 |
| 2020-01-05 | 938 | 7771 | 0 | 7837 | 2793 |

We may also want to see the revenue subtotals for each combination of date and salesman. We can pass an argument of `True` to the `margins` parameter to add totals for each row and column:

```
In [10] sales.pivot_table(
    index = "Date",
    columns = "Name",
    values = "Revenue",
    aggfunc = "sum",
    fill_value = 0,
    margins = True
)
```

```
Out [10]
```

| Name | Creed | Dwight | Jim | Michael | Oscar | All |
|---------------------|-------|--------|-------|---------|-------|--------|
| Date | | | | | | |
| 2020-01-01 00:00:00 | 4430 | 2639 | 1864 | 7172 | 9656 | 25761 |
| 2020-01-02 00:00:00 | 13214 | 0 | 8278 | 6362 | 8661 | 36515 |
| 2020-01-03 00:00:00 | 0 | 11912 | 4226 | 5982 | 7075 | 29195 |
| 2020-01-04 00:00:00 | 3144 | 0 | 6155 | 7917 | 2524 | 19740 |
| 2020-01-05 00:00:00 | 938 | 7771 | 0 | 7837 | 2793 | 19339 |
| All | 21726 | 22322 | 20523 | 35270 | 30709 | 130550 |

Notice that the inclusion of "All" in the row labels changes the visual representation of the dates, which now include the hour, minute, and second. Pandas needs to support both dates and string index labels. A string is the only data type that can represent either a date or a text value. Thus, the library converts the index from a `DatetimeIndex` for dates to a plain `Index` for strings. When converting a datetime object to its string representation, pandas includes the time; it also assumes the start of the day for a date without time.

We can use the `margins_name` parameter to customize the subtotal labels. The next example changes the labels from "All" to "Total":

```
In [11] sales.pivot_table(
    index = "Date",
    columns = "Name",
    values = "Revenue",
    aggfunc = "sum",
    fill_value = 0,
    margins = True,
    margins_name = "Total"
)
```

```
Out [11]
```

| Name Date | Creed | Dwight | Jim | Michael | Oscar | Total |
|---------------------|-------|--------|-------|---------|-------|--------|
| 2020-01-01 00:00:00 | 4430 | 2639 | 1864 | 7172 | 9656 | 25761 |
| 2020-01-02 00:00:00 | 13214 | 0 | 8278 | 6362 | 8661 | 36515 |
| 2020-01-03 00:00:00 | 0 | 11912 | 4226 | 5982 | 7075 | 29195 |
| 2020-01-04 00:00:00 | 3144 | 0 | 6155 | 7917 | 2524 | 19740 |
| 2020-01-05 00:00:00 | 938 | 7771 | 0 | 7837 | 2793 | 19339 |
| Total | 21726 | 22322 | 20523 | 35270 | 30709 | 130550 |

Ideally, Excel users will feel right at home with these options.

8.2.2 Additional options for pivot tables

A pivot table supports a variety of aggregation operations. Suppose that we're interested in the number of business deals closed per day. We can pass `aggfunc` an argument of "count" to count the number of sales rows for each combination of date and employee:

```
In [12] sales.pivot_table(  
        index = "Date",  
        columns = "Name",  
        values = "Revenue",  
        aggfunc = "count"  
)
```

```
Out [12]
```

| Name Date | Creed | Dwight | Jim | Michael | Oscar |
|--------------|-------|--------|-----|---------|-------|
| 2020-01-01 | 1.0 | 1.0 | 1.0 | 1.0 | 2.0 |
| 2020-01-02 | 2.0 | NaN | 1.0 | 1.0 | 1.0 |
| 2020-01-03 | NaN | 3.0 | 1.0 | 1.0 | 1.0 |
| 2020-01-04 | 1.0 | NaN | 2.0 | 1.0 | 1.0 |
| 2020-01-05 | 1.0 | 1.0 | NaN | 1.0 | 1.0 |

Once again, a `NaN` value indicates that the salesman did not make a sale on a given day. Creed did not close a single sale on 2020-01-03, for example, whereas Dwight closed three. Some additional options for the `aggfunc` parameter are listed in the following table:

| Argument | Description |
|---------------------|--|
| <code>max</code> | The largest value in the grouping |
| <code>min</code> | The smallest value in the grouping |
| <code>std</code> | The standard deviation of the values in the grouping |
| <code>median</code> | The median (midpoint) of the values in the grouping |
| <code>size</code> | The number of values in the grouping (equivalent to <code>count</code>) |

We can also pass a list of aggregation functions to the `pivot_table` function's `aggfunc` parameter. The pivot table will create a `MultiIndex` on the column axis and store the aggregations in its outermost level. The next example aggregates both the sum of revenue by date and the count of revenue by date:

```
In [13] sales.pivot_table(
    index = "Date",
    columns = "Name",
    values = "Revenue",
    aggfunc = ["sum", "count"],
    fill_value = 0
)

Out [13]
```

| Name Date | sum | | | | count | | | | | |
|--------------|-------|--------|------|---------|-------|-------|--------|-----|---------|-------|
| | Creed | Dwight | Jim | Michael | Oscar | Creed | Dwight | Jim | Michael | Oscar |
| | | | | | | | | | | |
| 2020-01-01 | 4430 | 2639 | 1864 | 7172 | 9656 | 1 | 1 | 1 | 1 | 2 |
| 2020-01-02 | 13214 | 0 | 8278 | 6362 | 8661 | 2 | 0 | 1 | 1 | 1 |
| 2020-01-03 | 0 | 11912 | 4226 | 5982 | 7075 | 0 | 3 | 1 | 1 | 1 |
| 2020-01-04 | 3144 | 0 | 6155 | 7917 | 2524 | 1 | 0 | 2 | 1 | 1 |
| 2020-01-05 | 938 | 7771 | 0 | 7837 | 2793 | 1 | 1 | 0 | 1 | 1 |

We can apply different aggregations to different columns by passing a dictionary to the `aggfunc` parameter. Use the dictionary's keys to identify `DataFrame` columns and the values to set the aggregation. The next example extracts the minimum revenue and the maximum expense for each combination of date and salesman:

```
In [14] sales.pivot_table(
    index = "Date",
    columns = "Name",
    values = ["Revenue", "Expenses"],
    fill_value = 0,
    aggfunc = { "Revenue": "min", "Expenses": "max" }
)

Out [14]
```

| Name Date | Expenses | | | | | Revenue | | | | |
|--------------|----------|--------|------|---------|-------|---------|--------|------|---------|-------|
| | Creed | Dwight | Jim | Michael | Oscar | Creed | Dwight | Jim | Michael | Oscar |
| | | | | | | | | | | |
| 20... | 548 | 368 | 1305 | 412 | 531 | 4430 | 2639 | 1864 | 7172 | 5250 |
| 20... | 1768 | 0 | 462 | 685 | 1401 | 8026 | 0 | 8278 | 6362 | 8661 |
| 20... | 0 | 758 | 1923 | 1772 | 906 | 0 | 4951 | 4226 | 5982 | 7075 |
| 20... | 1314 | 0 | 426 | 1857 | 1767 | 3144 | 0 | 3868 | 7917 | 2524 |
| 20... | 1053 | 1475 | 0 | 1633 | 624 | 938 | 7771 | 0 | 7837 | 2793 |

We can also stack multiple groupings on a single axis by passing the `index` parameter a list of columns. The next example aggregates the sum of expenses by salesman and date on the row axis. Pandas return a `DataFrame` with a two-level `MultiIndex`:

```
In [15] sales.pivot_table(
    index = ["Name", "Date"], values = "Revenue", aggfunc = "sum"
).head(10)
```

```
Out [15]
```

| Revenue | | |
|---------|------------|-------|
| Name | Date | |
| Creed | 2020-01-01 | 4430 |
| | 2020-01-02 | 13214 |
| | 2020-01-04 | 3144 |
| | 2020-01-05 | 938 |
| | 2020-01-01 | 2639 |
| Dwight | 2020-01-03 | 11912 |
| | 2020-01-05 | 7771 |
| | 2020-01-01 | 1864 |
| Jim | 2020-01-02 | 8278 |
| | 2020-01-03 | 4226 |

Switch the order of strings in the index list to rearrange the levels in the pivot table's MultiIndex. The next example swaps the positions of Name and Date:

```
In [16] sales.pivot_table(
    index = ["Date", "Name"], values = "Revenue", aggfunc = "sum"
).head(10)
```

```
Out [16]
```

| Revenue | | |
|------------|---------|-------|
| Date | Name | |
| 2020-01-01 | Creed | 4430 |
| | Dwight | 2639 |
| | Jim | 1864 |
| | Michael | 7172 |
| | Oscar | 9656 |
| 2020-01-02 | Creed | 13214 |
| | Jim | 8278 |
| | Michael | 6362 |
| | Oscar | 8661 |
| 2020-01-03 | Dwight | 11912 |

The pivot table first organizes and sorts the Date values, and then organizes and sorts the Name values within each Date.

8.3 Stacking and unstacking index levels

Here's a reminder of what sales looks like currently:

```
In [17] sales.head()
```

```
Out [17]
```

| | Date | Name | Customer | Revenue | Expenses |
|---|------------|-------|---------------|---------|----------|
| 0 | 2020-01-01 | Oscar | Logistics XYZ | 5250 | 531 |
| 1 | 2020-01-01 | Oscar | Money Corp. | 4406 | 661 |
| 2 | 2020-01-02 | Oscar | PaperMaven | 8661 | 1401 |
| 3 | 2020-01-03 | Oscar | PaperGenius | 7075 | 906 |
| 4 | 2020-01-04 | Oscar | Paper Pound | 2524 | 1767 |

Let's pivot sales to organize revenue by employee name and date. We'll place dates on the column axis and names on the row axis:

```
In [18] by_name_and_date = sales.pivot_table(
    index = "Name",
    columns = "Date",
    values = "Revenue",
    aggfunc = "sum"
)
by_name_and_date.head(2)

Out [18]

Date      2020-01-01  2020-01-02  2020-01-03  2020-01-04  2020-01-05
Name
Creed        4430.0     13214.0        NaN      3144.0      938.0
Dwight       2639.0         NaN     11912.0        NaN      7771.0
```

Sometimes, we may want to move an index level from one axis to another. This change offers a different presentation of the data, and we can decide which view we like better.

The `stack` method moves an index level from the column axis to the row axis. The next example moves the Date index level from the column axis to the row axis. Pandas creates a `MultiIndex` to store the two row levels: Name and Date. Because only one column of values remains, pandas returns a `Series`:

```
In [19] by_name_and_date.stack().head(7)

Out [19]

Name      Date
Creed    2020-01-01    4430.0
          2020-01-02    13214.0
          2020-01-04    3144.0
          2020-01-05    938.0
Dwight   2020-01-01    2639.0
          2020-01-03   11912.0
          2020-01-05   7771.0
dtype: float64
```

Notice that the `DataFrame`'s NaNs are absent from the `Series`. Pandas kept cells with NaNs in the `by_name_and_date` pivot table to maintain the structural integrity of the rows and columns. The shape of this `MultiIndex Series` allows pandas to discard the NaN values.

The complementary `unstack` method moves an index level from the row axis to the column axis. Consider the following pivot table, which groups revenue by customer and salesman. The row axis has a two-level `MultiIndex`, and the column axis has a regular index:

```
In [20] sales_by_customer = sales.pivot_table(
    index = ["Customer", "Name"],
    values = "Revenue",
```

```

        aggfunc = "sum"
    )

sales_by_customer.head()

Out [20]

```

| Customer | Name | Revenue | | | | |
|-------------------|---------|---------|--------|-------|---------|-------|
| | | Creed | Dwight | Jim | Michael | Oscar |
| Average Paper Co. | Creed | 13214 | | | | |
| | Jim | | 2287 | | | |
| Best Paper Co. | Dwight | | 2703 | | | |
| | Michael | | | 15754 | | |
| Logistics XYZ | Dwight | | | | 9209 | |

The unstack method moves the innermost level of the row index to the column index:

```

In [21] sales_by_customer.unstack()

Out [21]

```

| Customer | Name | Revenue | | | | |
|-------------------|---------|---------|--------|---------|---------|-------|
| | | Creed | Dwight | Jim | Michael | Oscar |
| | | | | | | |
| Average Paper Co. | 13214.0 | NaN | 2287.0 | NaN | NaN | NaN |
| Best Paper Co. | | 2703.0 | NaN | 15754.0 | NaN | NaN |
| Logistics XYZ | | 9209.0 | NaN | 7172.0 | 5250.0 | |
| Money Corp. | 5368.0 | NaN | 8278.0 | NaN | 4406.0 | |
| Paper Pound | | 7771.0 | 4226.0 | NaN | 5317.0 | |
| PaperGenius | | 2639.0 | 1864.0 | 12344.0 | 7075.0 | |
| PaperMaven | 3144.0 | NaN | 3868.0 | NaN | 8661.0 | |

In the new DataFrame, the column axis now has a two-level MultiIndex, and the row axis has a regular one-level index.

8.4 Melting a data set

A pivot table aggregates the values in a data set. In this section, we'll learn how to do the opposite: break an aggregated collection of data into an unaggregated one.

Let's apply our wide-versus-narrow framework to the sales DataFrame. Here's an effective strategy to figure out whether a data set is in narrow format: navigate across one row of values, and ask each cell whether its value is a single measurement of the variable that the column header is describing. Here's the first row of sales:

```

In [22] sales.head(1)

Out [22]

```

| Date | Name | Customer | Revenue | Expenses |
|------------|-------|---------------|---------|----------|
| 2020-01-01 | Oscar | Logistics XYZ | 5250 | 531 |

In the previous example, "2020-01-01" is a Date, "Oscar" is a Name, "Logistics XYZ" is a Customer, 5250 is a Revenue amount, and 531 is an Expenses amount. The sales DataFrame is an example of a narrow data set. Each row value represents a single observation for a given variable. No variable repeats across multiple columns.

We often have to choose between flexibility and readability when manipulating data in a wide or narrow format. We could represent the last four columns (Name, Customer, Revenue, Expenses) as fields in a single Category column (following example), but there is no real benefit because the four variables are distinct and separate. It is harder to aggregate data when it is stored in a format like this one:

| | Date | Category | Value |
|---|------------|----------|---------------|
| 0 | 2020-01-01 | Name | Oscar |
| 1 | 2020-01-01 | Customer | Logistics XYZ |
| 2 | 2020-01-01 | Revenue | 5250 |
| 3 | 2020-01-01 | Expenses | 531 |

The next data set, `video_game_sales.csv`, is a listing of regional sales for more than 16,000 video games. Each row includes the game's name as well as the number of units sold (in millions) in the North America (NA), Europe (EU), Japan (JP), and other (Other) regions:

```
In [23] video_game_sales = pd.read_csv("video_game_sales.csv")
video_game_sales.head()

Out [23]
```

| | Name | NA | EU | JP | Other |
|---|---------------------|-------|-------|-------|-------|
| 0 | Wii Sports | 41.49 | 29.02 | 3.77 | 8.46 |
| 1 | Super Mario Bros. | 29.08 | 3.58 | 6.81 | 0.77 |
| 2 | Mario Kart Wii | 15.85 | 12.88 | 3.79 | 3.31 |
| 3 | Wii Sports Resort | 15.75 | 11.01 | 3.28 | 2.96 |
| 4 | Pokemon Red/Poke... | 11.27 | 8.89 | 10.22 | 1.00 |

Once again, let's traverse a sample row and ask each cell whether it holds the correct piece of information. Here's the first row of `video_game_sales`:

```
In [24] video_game_sales.head(1)

Out [24]
```

| | Name | NA | EU | JP | Other |
|---|------------|-------|-------|------|-------|
| 0 | Wii Sports | 41.49 | 29.02 | 3.77 | 8.46 |

The first cell is fine; "Wii Sports" is an example of a Name. The next four cells are problematic. 41.49 is not a type of NA or a measurement of NA. NA (North America) is not a variable whose values vary throughout its column. The NA column's real piece of variable data is the sales numbers. NA represents the region for those sales numbers—a separate and distinct variable.

Thus, `video_game_sales` stores its data in wide format. Four columns (NA, EU, JP, and Other) store the same data point: the number of units sold. If we added more regional sales columns, the data set would grow horizontally. If we can group multiple column headers in a common category, it is a hint that the data set is storing its data in wide format.

Suppose that we moved the values "NA", "EU", "JP", and "Other" to a new Region column. Compare the preceding presentation with the following one:

| | Name | Region | Sales |
|---|------------|--------|-------|
| 0 | Wii Sports | NA | 41.49 |
| 1 | Wii Sports | EU | 29.02 |
| 2 | Wii Sports | JP | 3.77 |
| 3 | Wii Sports | Other | 8.46 |

In a way, we are unpivoting the video_game_sales DataFrame. We are converting an aggregate, summary view of the data to one in which each column stores one variable piece of information.

Pandas melts a DataFrame with the melt method. (*Melting* is the process of converting a wide data set to a narrow one.) The method accepts two primary parameters:

- The `id_vars` parameter sets the identifier column, the column for which the wide data set aggregates data. `Name` is the identifier column in `video_game_sales`. The data set aggregates sales per video game.
- The `value_vars` parameter accepts the column(s) whose values pandas will melt and store in a new column.

Let's start simple, melting only the `NA` column's values. In the next example, pandas loops through each `NA` column value and assigns it to a separate row in a new DataFrame. The library stores the former column name (`NA`) in a new variable column:

```
In [25] video_game_sales.melt(id_vars = "Name", value_vars = "NA").head()
Out [25]
```

| | Name | variable | value |
|---|------|--------------------------|----------|
| 0 | | Wii Sports | NA 41.49 |
| 1 | | Super Mario Bros. | NA 29.08 |
| 2 | | Mario Kart Wii | NA 15.85 |
| 3 | | Wii Sports Resort | NA 15.75 |
| 4 | | Pokemon Red/Pokemon Blue | NA 11.27 |

Next, let's melt all four of the regional sales columns. The next code sample passes the `value_vars` parameter a list of the four regional sales columns from `video_game_sales`:

```
In [26] regional_sales_columns = ["NA", "EU", "JP", "Other"]
        video_game_sales.melt(
            id_vars = "Name", value_vars = regional_sales_columns
        )
Out [26]
```

| | Name | variable | value |
|-------|------------------------------------|--------------------------|----------|
| 0 | | Wii Sports | NA 41.49 |
| 1 | | Super Mario Bros. | NA 29.08 |
| 2 | | Mario Kart Wii | NA 15.85 |
| 3 | | Wii Sports Resort | NA 15.75 |
| 4 | | Pokemon Red/Pokemon Blue | NA 11.27 |
| ... | | ... | ... |
| 66259 | Woody Woodpecker in Crazy Castle 5 | Other | 0.00 |
| 66260 | Men in Black II: Alien Escape | Other | 0.00 |

```

66261 SCORE International Baja 1000: The Official Game      Other    0.00
66262                           Know How 2                  Other    0.00
66263                           Spirits & Spells        Other    0.00

66264 rows × 3 columns

```

The `melt` method returns a DataFrame with 66,264 rows! By comparison, `video_game_sales` has 16,566 rows. The new data set is four times longer because it has four rows of data for each row in `video_games_sales`. The data set stores

- 16,566 rows for each video game and its respective NA sales number
- 16,566 rows for each video game and its respective EU sales number
- 16,566 rows for each video game and its respective JP sales number
- 16,566 rows for each video game and its respective Other sales number

The variable column holds the four regional column names from `video_game_sales`. The value column holds the values from those four regional sales columns. In the previous output, the data tells us that the videogame "Woody Woodpecker in Crazy Castle 5" had a value of 0.00 in the Other column of `video_game_sales`.

We can customize the melted DataFrame's column names by passing arguments to the `var_name` and `value_name` parameters. The next example uses `Region` for the variable column and `Sales` for the value column:

```

In [27] video_game_sales_by_region = video_game_sales.melt(
        id_vars = "Name",
        value_vars = regional_sales_columns,
        var_name = "Region",
        value_name = "Sales"
    )

video_game_sales_by_region.head()

```

Out [27]

| | Name | Region | Sales |
|---|--------------------------|--------|-------|
| 0 | Wii Sports | NA | 41.49 |
| 1 | Super Mario Bros. | NA | 29.08 |
| 2 | Mario Kart Wii | NA | 15.85 |
| 3 | Wii Sports Resort | NA | 15.75 |
| 4 | Pokemon Red/Pokemon Blue | NA | 11.27 |

Narrow data is easier to aggregate than wide data. Let's say we want to find the sum of each video game's sales across all regions. Given the melted data set, we can use the `pivot_table` method to accomplish this task with a few lines of code:

```

In [28] video_game_sales_by_region.pivot_table(
        index = "Name", values = "Sales", aggfunc = "sum"
    ).head()

```

Out [28]

| Name | Sales |
|-------------------------------|-------|
| '98 Koshien | 0.40 |
| .hack//G.U. Vol.1//Rebirth | 0.17 |
| .hack//G.U. Vol.2//Reminisce | 0.23 |
| .hack//G.U. Vol.3//Redemption | 0.17 |
| .hack//Infection Part 1 | 1.26 |

The data set's narrow shape simplified the process of pivoting it.

8.5 Exploding a list of values

Sometimes, a data set stores multiple values in the same cell. We may want to break up the data cluster so that each row stores a single value. Consider `recipes.csv`, a collection of three recipes, each of which has a name and an ingredients list. The ingredients are stored in a single comma-separated string:

```
In [29] recipes = pd.read_csv("recipes.csv")
      recipes
```

```
Out [29]
```

| | Recipe | Ingredients |
|---|-------------------------|---|
| 0 | Cashew Crusted Chicken | Apricot preserves, Dijon mustard, cu... |
| 1 | Tomato Basil Salmon | Salmon filets, basil, tomato, olive ... |
| 2 | Parmesan Cheese Chicken | Bread crumbs, Parmesan cheese, Italian... |

Do you recall the `str.split` method we introduced in chapter 6? This method uses a delimiter to split a string into substrings. We can split each `Ingredients` string by the presence of a comma. In the next example, pandas returns a `Series` of lists. Each list stores the ingredients for the row:

```
In [30] recipes["Ingredients"].str.split(",")
```

```
Out [30]
```

```
0    [Apricot preserves, Dijon mustard, curry pow...
1    [Salmon filets, basil, tomato, olive oil, ...
2    [Bread crumbs, Parmesan cheese, Italian seas...
Name: Ingredients, dtype: object
```

Let's overwrite the original `Ingredients` column with the new one:

```
In [31] recipes["Ingredients"] = recipes["Ingredients"].str.split(",")
      recipes
```

```
Out [31]
```

| | Recipe | Ingredients |
|---|-------------------------|--|
| 0 | Cashew Crusted Chicken | [Apricot preserves, Dijon mustard, ... |
| 1 | Tomato Basil Salmon | [Salmon filets, basil, tomato, ol... |
| 2 | Parmesan Cheese Chicken | [Bread crumbs, Parmesan cheese, It... |

Now, how can we spread out each list's values across multiple rows? The `explode` method creates a separate row for each list element in a `Series`. We invoke the method on a `DataFrame` and pass in the column with lists:

```
In [32] recipes.explode("Ingredients")
Out [32]
```

| | Recipe | Ingredients |
|---|------------------------|-------------------|
| 0 | Cashew Crusted Chicken | Apricot preserves |
| 0 | Cashew Crusted Chicken | Dijon mustard |
| 0 | Cashew Crusted Chicken | curry powder |
| 0 | Cashew Crusted Chicken | chicken breasts |
| 0 | Cashew Crusted Chicken | cashews |
| 1 | Tomato Basil Salmon | Salmon filets |
| 1 | Tomato Basil Salmon | basil |
| 1 | Tomato Basil Salmon | tomato |
| 1 | Tomato Basil Salmon | olive oil |
| 1 | Tomato Basil Salmon | Parmesan cheese |
| 2 | Simply Parmesan Cheese | Bread crumbs |
| 2 | Simply Parmesan Cheese | Parmesan cheese |
| 2 | Simply Parmesan Cheese | Italian seasoning |
| 2 | Simply Parmesan Cheese | egg |
| 2 | Simply Parmesan Cheese | chicken breasts |

Beautiful! We've isolated each ingredient to a separate line. Note that the `explode` method requires a `Series` of lists to work properly.

8.6 Coding challenge

Here's an opportunity to practice the reshaping, pivoting, and melting concepts introduced in this chapter.

8.6.1 Problems

We have two data sets for you to play with. The `used_cars.csv` file is a listing of used cars for sale on the classifieds website Craigslist. Each row includes the car's manufacturer, year of production, fuel type, transmission type, and price:

```
In [33] cars = pd.read_csv("used_cars.csv")
cars.head()
Out [33]
```

| | Manufacturer | Year | Fuel | Transmission | Price |
|---|--------------|------|------|--------------|-------|
| 0 | Acura | 2012 | Gas | Automatic | 10299 |
| 1 | Jaguar | 2011 | Gas | Automatic | 9500 |
| 2 | Honda | 2004 | Gas | Automatic | 3995 |
| 3 | Chevrolet | 2016 | Gas | Automatic | 41988 |
| 4 | Kia | 2015 | Gas | Automatic | 12995 |

The `minimum_wage.csv` data set is a collection of minimum wages across the United States. The data set has a `State` column and multiple year columns:

```
In [34] min_wage = pd.read_csv("minimum_wage.csv")
min_wage.head()

Out [34]
```

| | State | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 |
|---|------------|------|------|------|------|------|------|-------|-------|
| 0 | Alabama | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 1 | Alaska | 8.90 | 8.63 | 8.45 | 8.33 | 8.20 | 9.24 | 10.17 | 10.01 |
| 2 | Arizona | 8.33 | 8.18 | 8.34 | 8.38 | 8.36 | 8.50 | 8.40 | 10.22 |
| 3 | Arkansas | 7.18 | 6.96 | 6.82 | 6.72 | 6.61 | 7.92 | 8.35 | 8.68 |
| 4 | California | 9.19 | 8.91 | 8.72 | 8.60 | 9.52 | 9.51 | 10.43 | 10.22 |

Here are the challenges:

- 1 Aggregate the sum of car prices in cars. Group the results by fuel type on the row axis.
- 2 Aggregate the count of cars in cars. Group the results by manufacturer on the index axis and transmission type on the column axis. Show the subtotals for both the rows and columns.
- 3 Aggregate the average of car prices in cars. Group the results by year and fuel type on the index axis and transmission type on the column axis.
- 4 Given a DataFrame from the preceding challenge, move the transmission level from the column axis to the row axis.
- 5 Convert the min_wage from wide format to narrow format. In other words, move the data from the eight year columns (2010–17) to a single column.

8.6.2 Solutions

Let's tackle the problems one by one:

- 1 The `pivot_table` method is an optimal solution for adding the values in the Price column and organizing the totals by fuel type. We can use the method's `index` parameter to set the pivot table's index labels; we'll pass an argument of "Fuel". We'll specify the aggregation operation as "sum" with the `aggfunc` parameter:

```
In [35] cars.pivot_table(
    values = "Price", index = "Fuel", aggfunc = "sum"
)
```

Out [35]

| Fuel | Price |
|----------|-------------|
| Diesel | 986177143 |
| Electric | 18502957 |
| Gas | 86203853926 |
| Hybrid | 44926064 |
| Other | 242096286 |

- 2 We can also use the `pivot_table` method to count cars by manufacturer and transmission type. We'll use the `columns` parameter to set the `Transmission` column's values as the pivot table's column labels. Remember to pass the `margins` parameter an argument of `True` to show subtotals for rows and columns:

```
In [36] cars.pivot_table(
    values = "Price",
    index = "Manufacturer",
    columns = "Transmission",
    aggfunc = "count",
    margins = True
).tail()

Out [36]
Transmission   Automatic   Manual   Other   All
Manufacturer

```

| | Automatic | Manual | Other | All |
|------------|-----------|---------|---------|--------|
| Tesla | 179.0 | NaN | 59.0 | 238 |
| Toyota | 31480.0 | 1367.0 | 2134.0 | 34981 |
| Volkswagen | 7985.0 | 1286.0 | 236.0 | 9507 |
| Volvo | 2665.0 | 155.0 | 50.0 | 2870 |
| All | 398428.0 | 21005.0 | 21738.0 | 441171 |

- 3 To organize average car prices by year and fuel type on the pivot table's row axis, we can pass a list of strings to the `pivot_table` function's `index` parameter:

```
In [37] cars.pivot_table(
    values = "Price",
    index = ["Year", "Fuel"],
    columns = ["Transmission"],
    aggfunc = "mean"
)

Out [37]
Transmission   Automatic   Manual   Other
Year Fuel

```

| | Automatic | Manual | Other |
|---------------|--------------|--------------|--------------|
| 2000 Diesel | 11326.176962 | 14010.164021 | 11075.000000 |
| 2000 Electric | 1500.000000 | NaN | NaN |
| 2000 Gas | 4314.675996 | 6226.140327 | 3203.538462 |
| 2000 Hybrid | 2600.000000 | 2400.000000 | NaN |
| 2000 Other | 16014.918919 | 11361.952381 | 12984.642857 |
| | ... | ... | ... |
| 2020 Diesel | 63272.595930 | 1.000000 | 1234.000000 |
| 2020 Electric | 8015.166667 | 2200.000000 | 20247.500000 |
| 2020 Gas | 34925.857933 | 36007.270833 | 20971.045455 |
| 2020 Hybrid | 35753.200000 | NaN | 1234.000000 |
| 2020 Other | 22210.306452 | NaN | 2725.925926 |

102 rows × 3 columns

Let's assign the previous pivot table to a `report` variable for the next challenge:

```
In [38] report = cars.pivot_table(
    values = "Price",
    index = ["Year", "Fuel"],
```

```

        columns = ["Transmission"],
        aggfunc = "mean"
    )

```

- 4 The next exercise is to move the transmission type from the column index to the row index. The `stack` method does the trick here. The method returns a `MultiIndex Series`. The Series has three levels: Year, Fuel, and the newly added Transmission:

```
In [39] report.stack()

Out [39]

Year   Fuel      Transmission
2000 Diesel    Automatic      11326.176962
                  Manual       14010.164021
                  Other        11075.000000
                Electric    Automatic      1500.000000
                  Gas         Automatic     4314.675996
                                         ...
2020  Gas        Other        20971.045455
      Hybrid    Automatic      35753.200000
                  Other        1234.000000
                  Other        22210.306452
                  Other        2725.925926
Length: 274, dtype: float64
```

- 5 Next, we'd like to convert the `min_wage` data set from wide format to narrow format. Eight columns store the same variable: the wages themselves. The solution is the `melt` method. We can declare the `State` column as the identifier column and the eight year columns as the variable columns:

```
In [40] year_columns = [
    "2010", "2011", "2012", "2013",
    "2014", "2015", "2016", "2017"
]

min_wage.melt(id_vars = "State", value_vars = year_columns)

Out [40]
```

| | State | variable | value |
|-----|---------------|-----------------|--------------|
| 0 | Alabama | 2010 | 0.00 |
| 1 | Alaska | 2010 | 8.90 |
| 2 | Arizona | 2010 | 8.33 |
| 3 | Arkansas | 2010 | 7.18 |
| 4 | California | 2010 | 9.19 |
| ... | ... | ... | ... |
| 435 | Virginia | 2017 | 7.41 |
| 436 | Washington | 2017 | 11.24 |
| 437 | West Virginia | 2017 | 8.94 |
| 438 | Wisconsin | 2017 | 7.41 |
| 439 | Wyoming | 2017 | 5.26 |

440 rows × 3 columns

Here's a bonus tip: we can remove the `value_vars` parameter from the `melt` method invocation and still get the same DataFrame. By default, pandas melts data from all columns except the one we pass to the `id_vars` parameter:

```
In [41] min_wage.melt(id_vars = "State")
```

```
Out [41]
```

| | State | variable | value |
|-----|---------------|----------|-------|
| 0 | Alabama | 2010 | 0.00 |
| 1 | Alaska | 2010 | 8.90 |
| 2 | Arizona | 2010 | 8.33 |
| 3 | Arkansas | 2010 | 7.18 |
| 4 | California | 2010 | 9.19 |
| ... | ... | ... | ... |
| 435 | Virginia | 2017 | 7.41 |
| 436 | Washington | 2017 | 11.24 |
| 437 | West Virginia | 2017 | 8.94 |
| 438 | Wisconsin | 2017 | 7.41 |
| 439 | Wyoming | 2017 | 5.26 |

```
440 rows × 3 columns
```

We can also customize the column names with the `var_name` and `value_name` parameters. The next example uses "Year" and "Wage" to better explain what each column represents:

```
In [42] min_wage.melt(
        id_vars = "State", var_name = "Year", value_name = "Wage"
    )
```

```
Out [42]
```

| | State | Year | Wage |
|-----|---------------|------|-------|
| 0 | Alabama | 2010 | 0.00 |
| 1 | Alaska | 2010 | 8.90 |
| 2 | Arizona | 2010 | 8.33 |
| 3 | Arkansas | 2010 | 7.18 |
| 4 | California | 2010 | 9.19 |
| ... | ... | ... | ... |
| 435 | Virginia | 2017 | 7.41 |
| 436 | Washington | 2017 | 11.24 |
| 437 | West Virginia | 2017 | 8.94 |
| 438 | Wisconsin | 2017 | 7.41 |
| 439 | Wyoming | 2017 | 5.26 |

```
440 rows × 3 columns
```

Congratulations on completing the coding challenge!

Summary

- The `pivot_table` method aggregates a DataFrame's data.
- Pivot table aggregations include sum, count, and average.
- We can customize the pivot table's row labels and column labels.

- We can use one or more columns' values as the index labels of the pivot table.
- The `stack` method moves an index level from the column index to the row index.
- The `unstack` method moves an index level from the row index to the column index.
- The `melt` method “unpivots” an aggregated table by distributing its data across individual rows. The process converts a wide data set to a narrow one.
- The `explode` method creates a separate row entry for each element in a list; it requires a `Series` of lists.



The GroupBy object

This chapter covers

- Splitting a DataFrame into groups by using the groupby method
- Extracting first and last rows from groups in a GroupBy object
- Performing aggregate operations on GroupBy groups
- Iterating over DataFrames in a GroupBy object

The pandas library's GroupBy object is a storage container for grouping DataFrame rows into buckets. It provides a set of methods to aggregate and analyze each independent group in the collection. It allows us to extract rows at specific index positions within each group. It also offers a convenient way to iterate over the groups of rows. There's lots of power packed into a GroupBy object, so let's see what it's capable of doing.

9.1 Creating a GroupBy object from scratch

Let's create a new Jupyter Notebook and import the pandas library:

```
In [1] import pandas as pd
```

We'll kick things off with a small example and dive into more of the technical details in section 9.2. Let's begin by creating a DataFrame that stores the prices of fruits and vegetables in a supermarket:

```
In [2] food_data = {
    "Item": ["Banana", "Cucumber", "Orange", "Tomato", "Watermelon"],
    "Type": ["Fruit", "Vegetable", "Fruit", "Vegetable", "Fruit"],
    "Price": [0.99, 1.25, 0.25, 0.33, 3.00]
}

supermarket = pd.DataFrame(data = food_data)

supermarket
```

| | Item | Type | Price |
|---|------------|-----------|-------|
| 0 | Banana | Fruit | 0.99 |
| 1 | Cucumber | Vegetable | 1.25 |
| 2 | Orange | Fruit | 0.25 |
| 3 | Tomato | Vegetable | 0.33 |
| 4 | Watermelon | Fruit | 3.00 |

Out [2]

The Type column identifies the group to which an Item belongs. There are two groups of items in the supermarket data set: fruits and vegetables. We can use terms such as *groups*, *buckets*, and *clusters* interchangeably to describe the same idea. Multiple rows fall into the same category.

The GroupBy object organizes DataFrame rows into buckets based on shared values in a column. Suppose that we are interested in the average price of a fruit and the average price of a vegetable. If we could isolate the "Fruit" rows and "Vegetable" rows into separate groups, it would be easier to perform the calculations.

Let's begin by invoking the `groupby` method on the supermarket DataFrame. We need to pass it the column whose values pandas will use to create the groups. The next example provides the Type column. The method returns an object we haven't seen yet: a DataFrameGroupBy. The DataFrameGroupBy object is separate and distinct from a DataFrame:

```
In [3] groups = supermarket.groupby("Type")
groups

Out [3] <pandas.core.groupby.generic.DataFrameGroupBy object at
0x114f2db90>
```

The Type column has two unique values, so the GroupBy object will store two groups. The get_group method accepts a group name and returns a DataFrame with the corresponding rows. Let's pull out the "Fruit" rows:

```
In [4] groups.get_group("Fruit")
Out [4]
```

| | Item | Type | Price |
|---|------------|-------|-------|
| 0 | Banana | Fruit | 0.99 |
| 2 | Orange | Fruit | 0.25 |
| 4 | Watermelon | Fruit | 3.00 |

We can also pull out the "Vegetable" rows:

```
In [5] groups.get_group("Vegetable")
Out [5]
```

| | Item | Type | Price |
|---|----------|-----------|-------|
| 1 | Cucumber | Vegetable | 1.25 |
| 3 | Tomato | Vegetable | 0.33 |

The GroupBy object excels at aggregate operations. Our original goal was to calculate the average price of the fruits and vegetables in supermarket. We can invoke the mean method on groups to calculate the average price of items within each group. With a few lines of code, we've successfully split, aggregated, and analyzed a data set:

```
In [6] groups.mean()
Out [6]
      Price
Type
_____
Fruit      1.413333
Vegetable   0.790000
```

With the foundational knowledge under our belts, let's move on to a more complex data set.

9.2 *Creating a GroupBy object from a data set*

The Fortune 1000 is a listing of the 1,000 largest companies in the United States by revenue. The list is updated annually by the business magazine *Fortune*. The fortune1000.csv file is a collection of Fortune 1000 companies from 2018. Each row includes a company's name, revenue, profits, employee count, sector, and industry:

```
In [7] fortune = pd.read_csv("fortune1000.csv")
fortune
Out [7]
      Company    Revenues    Profits    Employees       Sector    Industry
0      Walmart  500343.0   9862.0   2300000  Retailing  General M...
1  Exxon Mobil  244363.0  19710.0     71200      Energy  Petroleum...
```

```

2    Berkshire...  242137.0  44940.0      377000  Financials  Insurance...
3          Apple   229234.0  48351.0      123000  Technology  Computers...
4    UnitedHea...  201159.0  10558.0      260000  Health Care  Health Ca...
...        ...     ...       ...       ...
995 SiteOne L...   1862.0    54.6       3664  Wholesalers  Wholesale...
996 Charles R...   1858.0   123.4      11800  Health Care  Health Ca...
997 CoreLogic    1851.0   152.2       5900  Business ...  Financial...
998 Ensign Group  1849.0   40.5      21301  Health Care  Health Ca...
999      HCP      1848.0   414.2       190   Financials  Real estate

```

1000 rows × 6 columns

A sector can have many companies. Apple and Amazon.com both belong to the "Technology" sector, for example.

An industry is a subcategory within a sector. The "Pipelines" and "Petroleum Refining" industries fall in the "Energy" sector, for example.

The Sector column holds 21 unique sectors. Suppose that we want to find the average revenue across the companies within each sector. Before we use the GroupBy object, let's solve the problem by taking an alternative approach. Chapter 5 showed us how to create a Boolean Series to extract a subset of rows from a DataFrame. The next example pulls out all companies with a Sector value of "Retailing":

```
In [8] in_retailing = fortune["Sector"] == "Retailing"
       retail_companies = fortune[in_retailing]
       retail_companies.head()
```

Out [8]

| | Company | Revenues | Profits | Employees | Sector | Industry |
|----|------------|----------|---------|-----------|-----------|-------------------|
| 0 | Walmart | 500343.0 | 9862.0 | 2300000 | Retailing | General Mercha... |
| 7 | Amazon.com | 177866.0 | 3033.0 | 566000 | Retailing | Internet Servi... |
| 14 | Costco | 129025.0 | 2679.0 | 182000 | Retailing | General Mercha... |
| 22 | Home Depot | 100904.0 | 8630.0 | 413000 | Retailing | Specialty Reta... |
| 38 | Target | 71879.0 | 2934.0 | 345000 | Retailing | General Mercha... |

We can pull out the Revenues column from the subset by using square brackets:

```
In [9] retail_companies["Revenues"].head()
Out [9] 0      500343.0
         7      177866.0
        14     129025.0
        22     100904.0
        38      71879.0
Name: Revenues, dtype: float64
```

Finally, we can calculate the Retailing sector's average revenue by invoking the mean method on the Revenues column:

```
In [10] retail_companies["Revenues"].mean()
Out [10] 21874.714285714286
```

The preceding code is suitable for calculating the average revenue of one sector. We'll need to write a lot of additional code, however, to apply the same logic to the other 20

sectors in `fortune`. The code is not particularly scalable. Python can automate some of the repetition, but the `GroupBy` object offers the best solution out of the box. The pandas developers have already solved this problem for us.

Let's invoke the `groupby` method on the `fortune` `DataFrame`. The method accepts the column whose values pandas will use to group the rows. A column is a good candidate for a grouping if it stores categorical data for the rows. Make sure that there are parent categories under which multiple rows fall. The data set has 1,000 unique companies but only 21 unique sectors, for example, so the `Sector` column is a good fit for aggregate analysis:

```
In [11] sectors = fortune.groupby("Sector")
```

Let's output the `sectors` variable to see what kind of object we're working with:

```
In [12] sectors
```

```
Out [12] <pandas.core.groupby.generic.DataFrameGroupBy object at  
0x1235b1d10>
```

A `DataFrameGroupBy` object is a bundle of `DataFrames`. Behind the scenes, pandas repeated the extraction process we used for the "Retailing" sector but for all 21 values in the `Sector` column.

We can count the number of groups in `sectors` by passing the `GroupBy` object into Python's built-in `len` function:

```
In [13] len(sectors)
```

```
Out [13] 21
```

The `sectors` `GroupBy` object has 21 `DataFrames`. The number is equal to the number of unique values in `fortune`'s `Sector` column, which we can discover by invoking the `nunique` method:

```
In [14] fortune["Sector"].nunique()
```

```
Out [14] 21
```

What are the 21 sectors, and how many companies from `fortune` belong to each one? The `size` method on the `GroupBy` object returns a `Series` with an alphabetical list of the groups and their row counts. The following output tells us that 25 `fortune` companies have a `Sector` value of "Aerospace & Defense", 14 have a value of "Apparel", and so on:

```
In [15] sectors.size()
```

```
Out [15] Sector  
Aerospace & Defense    25  
Apparel                 14  
Business Services        53  
Chemicals                33  
Energy                  107
```

```

Engineering & Construction      27
Financials                      155
Food & Drug Stores              12
Food, Beverages & Tobacco       37
Health Care                     71
Hotels, Restaurants & Leisure  26
Household Products               28
Industrials                      49
Materials                        45
Media                            25
Motor Vehicles & Parts          19
Retailing                         77
Technology                       103
Telecommunications                10
Transportation                   40
Wholesalers                      44
dtype: int64

```

Now that we've bucketed our fortune rows, let's explore what we can do with a GroupBy object.

9.3 Attributes and methods of a GroupBy object

One way to visualize our GroupBy object is as a dictionary that maps the 21 sectors to a collection of fortune rows belonging to each one. The `groups` attribute stores a dictionary with these group-to-row associations; its keys are sector names, and its values are `Index` objects storing the row index positions from the fortune `DataFrame`. The dictionary has 21 total key-value pairs, but I've limited the following output to the first two pairs to save space:

```

In [16] sectors.groups

Out [16]

'Aerospace & Defense': Int64Index([ 26,  50,  58,  98, 117, 118, 207, 224,
                                         275, 380, 404, 406, 414, 540, 660,
                                         661, 806, 829, 884, 930, 954, 955,
                                         959, 975, 988], dtype='int64'),
'Apparel': Int64Index([88, 241, 331, 420, 432, 526, 529, 554, 587, 678,
                       766, 774, 835, 861], dtype='int64'),

```

The output tells us that rows with index positions 26, 50, 58, 98, and so on have a value of "Aerospace & Defense" in fortune's Sector column.

Chapter 4 introduced the `loc` accessor for extracting `DataFrame` rows and columns by index label. Its first argument is the row index label, and its second argument is the column index label. Let's extract a sample fortune row to confirm that pandas is pulling it into the correct sector group. We'll try 26, the first index position listed in the "Aerospace & Defense" group:

```

In [17] fortune.loc[26, "Sector"]

Out [17] 'Aerospace & Defense'

```

What if we want to find the highest-performing company (by revenue) within each sector? The `GroupBy` object's `first` method extracts the first row listed for each sector in `fortune`. Because our `fortune` `DataFrame` is sorted by revenue, the first company pulled out for each sector will be the highest-performing company within that sector. The return value of `first` is a 21-row `DataFrame` (one company per sector):

```
In [18] sectors.first()
```

```
Out [18]
```

| Sector | Company | Revenues | Profits | Employees | Industry |
|----------------|---------------|----------|---------|-----------|---------------|
| Aerospace &... | Boeing | 93392.0 | 8197.0 | 140800 | Aerospace ... |
| Apparel | Nike | 34350.0 | 4240.0 | 74400 | Apparel |
| Business Se... | ManpowerGroup | 21034.0 | 545.4 | 29000 | Temporary ... |
| Chemicals | DowDuPont | 62683.0 | 1460.0 | 98000 | Chemicals |
| Energy | Exxon Mobil | 244363.0 | 19710.0 | 71200 | Petroleum ... |
| ... | ... | ... | ... | ... | ... |
| Retailing | Walmart | 500343.0 | 9862.0 | 2300000 | General Me... |
| Technology | Apple | 229234.0 | 48351.0 | 123000 | Computers,... |
| Telecommuni... | AT&T | 160546.0 | 29450.0 | 254000 | Telecommun... |
| Transportation | UPS | 65872.0 | 4910.0 | 346415 | Mail, Pack... |
| Wholesalers | McKesson | 198533.0 | 5070.0 | 64500 | Wholesaler... |

The complementary `last` method extracts the last company from `fortune` that belongs to each sector. Again, pandas pulls the rows out in the order in which they appear in the `DataFrame`. Because `fortune` sorts companies in descending order by revenue, the following results reveal the companies with the lowest revenue per sector:

```
In [19] sectors.last()
```

```
Out [19]
```

| Sector | Company | Revenues | Profits | Employees | Industry |
|----------------|---------------|----------|---------|-----------|---------------|
| Aerospace &... | Aerojet Ro... | 1877.0 | -9.2 | 5157 | Aerospace ... |
| Apparel | Wolverine ... | 2350.0 | 0.3 | 3700 | Apparel |
| Business Se... | CoreLogic | 1851.0 | 152.2 | 5900 | Financial ... |
| Chemicals | Stepan | 1925.0 | 91.6 | 2096 | Chemicals |
| Energy | Superior E... | 1874.0 | -205.9 | 6400 | Oil and Ga... |
| ... | ... | ... | ... | ... | ... |
| Retailing | Childrens ... | 1870.0 | 84.7 | 9800 | Specialty ... |
| Technology | VeriFone S... | 1871.0 | -173.8 | 5600 | Financial ... |
| Telecommuni... | Zayo Group... | 2200.0 | 85.7 | 3794 | Telecommun... |
| Transportation | Echo Globa... | 1943.0 | 12.6 | 2453 | Transporta... |
| Wholesalers | SiteOne La... | 1862.0 | 54.6 | 3664 | Wholesaler... |

The `GroupBy` object assigns index positions to the rows in each sector group. The first `fortune` row in the "Aerospace & Defense" sector has an index position of 0 within its group. Likewise, the first `fortune` row in the "Apparel" sector has an index position of 0 within its group. The index positions are independent between groups.

The `nth` method extracts the row at a given index position within its group. If we invoke the `nth` method with an argument of 0, we get the first company within each sector. The next `DataFrame` is identical to the one returned by the `first` method:

```
In [20] sectors.nth(0)
```

```
Out [20]
```

| Sector | Company | Revenues | Profits | Employees | Industry |
|----------------|----------------|-----------------|----------------|------------------|-----------------|
| Aerospace &... | Boeing | 93392.0 | 8197.0 | 140800 | Aerospace ... |
| Apparel | Nike | 34350.0 | 4240.0 | 74400 | Apparel |
| Business Se... | ManpowerGroup | 21034.0 | 545.4 | 29000 | Temporary ... |
| Chemicals | DowDuPont | 62683.0 | 1460.0 | 98000 | Chemicals |
| Energy | Exxon Mobil | 244363.0 | 19710.0 | 71200 | Petroleum ... |
| ... | ... | ... | ... | ... | ... |
| Retailing | Walmart | 500343.0 | 9862.0 | 2300000 | General Me... |
| Technology | Apple | 229234.0 | 48351.0 | 123000 | Computers,... |
| Telecommuni... | AT&T | 160546.0 | 29450.0 | 254000 | Telecommun... |
| Transportation | UPS | 65872.0 | 4910.0 | 346415 | Mail, Pack... |
| Wholesalers | McKesson | 198533.0 | 5070.0 | 64500 | Wholesaler... |

The next example passes an argument of 3 to the nth method to pull out the fourth row from each sector in the fortune DataFrame. The results include the 21 companies that are ranked fourth-best by revenue in their sector:

```
In [21] sectors.nth(3)
```

```
Out [21]
```

| Sector | Company | Revenues | Profits | Employees | Industry |
|----------------|----------------|-----------------|----------------|------------------|-----------------|
| Aerospace &... | General Dy... | 30973.0 | 2912.0 | 98600 | Aerospace ... |
| Apparel | Ralph Lauren | 6653.0 | -99.3 | 18250 | Apparel |
| Business Se... | Aramark | 14604.0 | 373.9 | 215000 | Diversifie... |
| Chemicals | Monsanto | 14640.0 | 2260.0 | 21900 | Chemicals |
| Energy | Valero Energy | 88407.0 | 4065.0 | 10015 | Petroleum ... |
| ... | ... | ... | ... | ... | ... |
| Retailing | Home Depot | 100904.0 | 8630.0 | 413000 | Specialty ... |
| Technology | IBM | 79139.0 | 5753.0 | 397800 | Informatio... |
| Telecommuni... | Charter Co... | 41581.0 | 9895.0 | 94800 | Telecommun... |
| Transportation | Delta Air ... | 41244.0 | 3577.0 | 86564 | Airlines |
| Wholesalers | Sysco | 55371.0 | 1142.5 | 66500 | Wholesaler... |

Notice that the value for the "Apparel" sector is "Ralph Lauren". We can confirm the output is correct by filtering for the "Apparel" rows in fortune. Notice that "Ralph Lauren" is fourth in line:

```
In [22] fortune[fortune["Sector"] == "Apparel"].head()
```

```
Out [22]
```

| | Company | Revenues | Profits | Employees | Sector | Industry |
|-----|----------------|-----------------|----------------|------------------|---------------|-----------------|
| 88 | Nike | 34350.0 | 4240.0 | 74400 | Apparel | Apparel |
| 241 | VF | 12400.0 | 614.9 | 69000 | Apparel | Apparel |
| 331 | PVH | 8915.0 | 537.8 | 28050 | Apparel | Apparel |
| 420 | Ralph Lauren | 6653.0 | -99.3 | 18250 | Apparel | Apparel |
| 432 | Hanesbrands | 6478.0 | 61.9 | 67200 | Apparel | Apparel |

The head method extracts multiple rows from each group. In the next example, head(2) extracts the first two rows for each sector within fortune. The result is a DataFrame with 42 rows (21 unique sectors, with two rows for each sector). Don't confuse this head method on a GroupBy object with the head method on a DataFrame object:

```
In [23] sectors.head(2)
```

```
Out [23]
```

| | Company | Revenues | Profits | Employees | Sector | Industry |
|-----|--------------|----------|---------|-----------|--------------|--------------|
| 0 | Walmart | 500343.0 | 9862.0 | 2300000 | Retailing | General M... |
| 1 | Exxon Mobil | 244363.0 | 19710.0 | 71200 | Energy | Petroleum... |
| 2 | Berkshire... | 242137.0 | 44940.0 | 377000 | Financials | Insurance... |
| 3 | Apple | 229234.0 | 48351.0 | 123000 | Technology | Computers... |
| 4 | UnitedHea... | 201159.0 | 10558.0 | 260000 | Health Care | Health Ca... |
| ... | ... | ... | ... | ... | ... | ... |
| 160 | Visa | 18358.0 | 6699.0 | 15000 | Business ... | Financial... |
| 162 | Kimberly-... | 18259.0 | 2278.0 | 42000 | Household... | Household... |
| 163 | AECOM | 18203.0 | 339.4 | 87000 | Engineeri... | Engineeri... |
| 189 | Sherwin-W... | 14984.0 | 1772.3 | 52695 | Chemicals | Chemicals |
| 241 | VF | 12400.0 | 614.9 | 69000 | Apparel | Apparel |

The complementary tail method extracts the last rows from each group. tail(3) pulls the last three rows for each sector, for example. The result is a 63-row DataFrame (21 sectors x 3 rows):

```
In [24] sectors.tail(3)
```

```
Out [24]
```

| | Company | Revenues | Profits | Employees | Sector | Industry |
|-----|--------------|----------|---------|-----------|--------------|--------------|
| 473 | Windstrea... | 5853.0 | -2116.6 | 12979 | Telecommu... | Telecommu... |
| 520 | Telephone... | 5044.0 | 153.0 | 9900 | Telecommu... | Telecommu... |
| 667 | Weis Markets | 3467.0 | 98.4 | 23000 | Food & D... | Food and ... |
| 759 | Hain Cele... | 2853.0 | 67.4 | 7825 | Food, Bev... | Food Cons... |
| 774 | Fossil Group | 2788.0 | -478.2 | 12300 | Apparel | Apparel |
| ... | ... | ... | ... | ... | ... | ... |
| 995 | SiteOne L... | 1862.0 | 54.6 | 3664 | Wholesalers | Wholesale... |
| 996 | Charles R... | 1858.0 | 123.4 | 11800 | Health Care | Health Ca... |
| 997 | CoreLogic | 1851.0 | 152.2 | 5900 | Business ... | Financial... |
| 998 | Ensign Group | 1849.0 | 40.5 | 21301 | Health Care | Health Ca... |
| 999 | HCP | 1848.0 | 414.2 | 190 | Financials | Real estate |

```
63 rows × 6 columns
```

We can use the get_group method to extract all rows in a given group. The method returns a DataFrame containing the rows. The next example shows all companies in the "Energy" sector:

```
In [25] sectors.get_group("Energy").head()
```

```
Out [25]
```

| | Company | Revenues | Profits | Employees | Sector | Industry |
|----|-------------|----------|---------|-----------|--------|----------------|
| 1 | Exxon Mobil | 244363.0 | 19710.0 | 71200 | Energy | Petroleum R... |
| 12 | Chevron | 134533.0 | 9195.0 | 51900 | Energy | Petroleum R... |

```

27    Phillips 66    91568.0    5106.0      14600  Energy  Petroleum R...
30    Valero Energy   88407.0    4065.0      10015  Energy  Petroleum R...
40    Marathon Pe...   67610.0    3432.0      43800  Energy  Petroleum R...

```

Now that we understand a `GroupBy` object's mechanics, let's discuss how we can aggregate the values in every nested group.

9.4 Aggregate operations

We can invoke methods on the `GroupBy` object to apply aggregate operations to every nested group. The `sum` method, for example, adds the column values in each group. By default, pandas targets all numeric columns in the original `DataFrame`. In the next example, the `sum` method calculates the sum per sector for the three numeric columns (Revenues, Profits, and Employees) in the `fortune` `DataFrame`. We invoke the `sum` method on the `GroupBy` object:

```
In [26] sectors.sum().head(10)
```

```
Out [26]
```

| Sector | Revenues | Profits | Employees |
|----------------------------|-----------|----------|-----------|
| Aerospace & Defense | 383835.0 | 26733.5 | 1010124 |
| Apparel | 101157.3 | 6350.7 | 355699 |
| Business Services | 316090.0 | 37179.2 | 1593999 |
| Chemicals | 251151.0 | 20475.0 | 474020 |
| Energy | 1543507.2 | 85369.6 | 981207 |
| Engineering & Construction | 172782.0 | 7121.0 | 420745 |
| Financials | 2442480.0 | 264253.5 | 3500119 |
| Food & Drug Stores | 405468.0 | 8440.3 | 1398074 |
| Food, Beverages & Tobacco | 510232.0 | 54902.5 | 1079316 |
| Health Care | 1507991.4 | 92791.1 | 2971189 |

Let's double-check a sample calculation. Pandas lists the sum of company revenue in "Aerospace & Defense" as \$383,835. We can use the `get_group` method to retrieve the nested "Aerospace & Defense" `DataFrame`, target its Revenues column, and use the `sum` method to calculate its sum:

```
In [27] sectors.get_group("Aerospace & Defense").head()
```

```
Out [27]
```

| Company | Revenues | Profits | Employees | Sector | Industry |
|--------------|----------|---------|-----------|--------------|--------------|
| Boeing | 93392.0 | 8197.0 | 140800 | Aerospace... | Aerospace... |
| United Te... | 59837.0 | 4552.0 | 204700 | Aerospace... | Aerospace... |
| Lockheed ... | 51048.0 | 2002.0 | 100000 | Aerospace... | Aerospace... |
| General D... | 30973.0 | 2912.0 | 98600 | Aerospace... | Aerospace... |
| Northrop ... | 25803.0 | 2015.0 | 70000 | Aerospace... | Aerospace... |

```
In [28] sectors.get_group("Aerospace & Defense").loc[:, "Revenues"].head()
```

```
Out [28] 26      93392.0
          50      59837.0
          58      51048.0
```

```

98      30973.0
117     25803.0
Name: Revenues, dtype: float64

In [29] sectors.get_group("Aerospace & Defense").loc[:, "Revenues"].sum()

Out [29] 383835.0

```

The values are equal. Pandas is correct! With a single sum method call, the library applied the calculation logic to each nested DataFrame in the sectors GroupBy object. We've performed an aggregate analysis for all of a column's groups with a minimal amount of code.

The GroupBy object supports many other aggregation methods. The next example invokes the mean method to calculate the average of the Revenues, Profits, and Employees columns per sector. Again, pandas includes only numeric columns in its calculations:

```

In [30] sectors.mean().head()

Out [30]

```

| Sector | Revenues | Profits | Employees |
|---------------------|--------------|-------------|--------------|
| Aerospace & Defense | 15353.400000 | 1069.340000 | 40404.960000 |
| Apparel | 7225.521429 | 453.621429 | 25407.071429 |
| Business Services | 5963.962264 | 701.494340 | 30075.452830 |
| Chemicals | 7610.636364 | 620.454545 | 14364.242424 |
| Energy | 14425.300935 | 805.373585 | 9170.158879 |

We can target a single fortune column by passing its name inside square brackets after the GroupBy object. Pandas returns a new object, a SeriesGroupBy:

```

In [31] sectors["Revenues"]

Out [31] <pandas.core.groupby.generic.SeriesGroupBy object at 0x114778210>

```

Under the hood, the DataFrameGroupBy object stores a collection of SeriesGroupBy objects. The SeriesGroupBy objects can perform aggregate operations on individual columns from fortune. Pandas will organize the results by sector. The next example calculates the sum of revenue by sector:

```

In [32] sectors["Revenues"].sum().head()

Out [32] Sector
          Aerospace & Defense    383835.0
          Apparel           101157.3
          Business Services   316090.0
          Chemicals          251151.0
          Energy             1543507.2
Name: Revenues, dtype: float64

```

The next example calculates the average number of employees per sector:

```
In [33] sectors["Employees"].mean().head()

Out [33] Sector
Aerospace & Defense    40404.960000
Apparel                  25407.071429
Business Services         30075.452830
Chemicals                 14364.242424
Energy                   9170.158879
Name: Employees, dtype: float64
```

The `max` method returns the maximum value from a given column. In the next example, we extract the highest Profits column value for each sector. The best-performing company in the "Aerospace & Defense" sector has profits of \$8,197:

```
In [34] sectors["Profits"].max().head()

Out [34] Sector
Aerospace & Defense     8197.0
Apparel                  4240.0
Business Services          6699.0
Chemicals                 3000.4
Energy                   19710.0
Name: Profits, dtype: float64
```

The complementary `min` method returns the minimum value in a given column. The next example displays the minimum employee count per sector. The smallest number of employees at a company in the "Aerospace & Defense" sector is 5,157:

```
In [35] sectors["Employees"].min().head()

Out [35] Sector
Aerospace & Defense     5157
Apparel                  3700
Business Services          2338
Chemicals                 1931
Energy                   593
Name: Employees, dtype: int64
```

The `agg` method applies multiple aggregate operations to different columns and accepts a dictionary as its argument. In each key-value pair, the key denotes a Data-Frame column, and the value specifies the aggregate operation to apply to the column. The next example extracts the lowest revenue, highest profit, and average number of employees for each sector:

```
In [36] aggregations = {
    "Revenues": "min",
    "Profits": "max",
    "Employees": "mean"
}

sectors.agg(aggregations).head()
```

```
Out [36]
```

| Sector | Revenues | Profits | Employees |
|---------------------|----------|---------|--------------|
| Aerospace & Defense | 1877.0 | 8197.0 | 40404.960000 |
| Apparel | 2350.0 | 4240.0 | 25407.071429 |
| Business Services | 1851.0 | 6699.0 | 30075.452830 |
| Chemicals | 1925.0 | 3000.4 | 14364.242424 |
| Energy | 1874.0 | 19710.0 | 9170.158879 |

Pandas returns a DataFrame with the aggregation dictionary's keys as column headers. The sectors remain index labels.

9.5 Applying a custom operation to all groups

Suppose that we want to apply a custom operation to each nested group in a GroupBy object. In section 9.4, we used the GroupBy object's `max` method to find each sector's maximum revenue. Let's say we want to identify the company with the highest revenue in each sector. We solved this problem earlier, but let's now assume that `fortune` is unordered.

A DataFrame's `nlargest` method extracts the rows with the greatest value in a given column. Here's a quick refresher. The next example returns the five fortune rows with the greatest values in the Profits column:

```
In [37] fortune.nlargest(n = 5, columns = "Profits")
```

```
Out [37]
```

| Company | Revenues | Profits | Employees | Sector | Industry |
|-----------------|----------|---------|-----------|--------------|--------------|
| 3 Apple | 229234.0 | 48351.0 | 123000 | Technology | Computers... |
| 2 Berkshire... | 242137.0 | 44940.0 | 377000 | Financials | Insurance... |
| 15 Verizon | 126034.0 | 30101.0 | 155400 | Telecommu... | Telecommu... |
| 8 AT&T | 160546.0 | 29450.0 | 254000 | Telecommu... | Telecommu... |
| 19 JPMorgan ... | 113899.0 | 24441.0 | 252539 | Financials | Commercia... |

If we could invoke the `nlargest` method on each nested DataFrame in `sectors`, we'd get the results we seek. We'd get the company with the highest revenue in each sector.

We can use the GroupBy object's `apply` method here. The method expects a function as an argument. It invokes the function once for each group in the GroupBy object. Then it collects the return values from the function invocations and returns them in a new DataFrame.

First, let's define a `get_largest_row` function that accepts a single argument: a DataFrame. The function will return the DataFrame row with the greatest value in the `Revenues` column. The function is dynamic; it can perform the logic on any DataFrame as long as it has a `Revenues` column:

```
In [38] def get_largest_row(df):
        return df.nlargest(1, "Revenues")
```

Next, we can invoke the `apply` method and pass in the uninvoked `get_largest_row` function. Pandas invokes `get_largest_row` once for each sector and returns a DataFrame with the companies with the highest revenue in their sector:

```
In [39] sectors.apply(get_largest_row).head()
```

```
Out [39]
```

| Sector | | Company | Revenues | Profits | Employees | Industry |
|---------------|-----|--------------|----------|---------|-----------|--------------|
| Aerospace | ... | Boeing | 93392.0 | 8197.0 | 140800 | Aerospace... |
| Apparel | 88 | Nike | 34350.0 | 4240.0 | 74400 | Apparel |
| Business S... | 142 | ManpowerG... | 21034.0 | 545.4 | 29000 | Temporary... |
| Chemicals | 46 | DowDuPont | 62683.0 | 1460.0 | 98000 | Chemicals |
| Energy | 1 | Exxon Mobil | 244363.0 | 19710.0 | 71200 | Petroleum... |

Use the `apply` method when pandas does not support a custom aggregation you'd like to apply to each nested group.

9.6 Grouping by multiple columns

We can create a `GroupBy` object with values from multiple DataFrame columns. This operation is optimal when a combination of column values serves as the best identifier for a group. The next example passes a list of two strings to the `groupby` method. Pandas groups the rows first by the `Sector` column's values and then by the `Industry` column's values. Remember that a company's industry is a subcategory within a larger sector:

```
In [40] sector_and_industry = fortune.groupby(by = ["Sector", "Industry"])
```

The `GroupBy` object's `size` method now returns a `MultiIndex Series` with a count of rows for each internal group. This `GroupBy` object has a length of 82, which means that `fortune` has 82 unique combinations of sector and industry:

```
In [41] sector_and_industry.size()
```

```
Out [41]
```

| Sector | Industry | |
|---------------------|---|----|
| Aerospace & Defense | Aerospace and Defense | 25 |
| Apparel | Apparel | 14 |
| Business Services | Advertising, marketing | 2 |
| | Diversified Outsourcing Services | 14 |
| | Education | 2 |
| | | .. |
| Transportation | Trucking, Truck Leasing | 11 |
| Wholesalers | Wholesalers: Diversified | 24 |
| | Wholesalers: Electronics and Office Equipment | 8 |
| | Wholesalers: Food and Grocery | 6 |
| | Wholesalers: Health Care | 6 |

Length: 82, dtype: int64

The `get_group` method requires a tuple of values to extract a nested DataFrame from the `GroupBy` collection. The next example targets rows with a sector of "Business Services" and industry of "Education":

```
In [42] sector_and_industry.get_group(("Business Services", "Education"))

Out [42]
```

| | Company | Revenues | Profits | Employees | Sector | Industry |
|-----|----------------|-----------------|----------------|------------------|---------------|-----------------|
| 567 | Laureate ... | 4378.0 | 91.5 | 54500 | Business ... | Education |
| 810 | Graham Ho... | 2592.0 | 302.0 | 16153 | Business ... | Education |

For all aggregations, pandas returns a MultiIndex DataFrame with the calculations. The next example calculates the sum of the three numeric columns in `fortune` (`Revenues`, `Profits`, and `Employees`), grouped first by sector and then by the industries within each sector:

```
In [43] sector_and_industry.sum().head()

Out [43]
```

| Sector | Industry | Revenues | Profits | Employees |
|---------------------|----------------------|-----------------|----------------|------------------|
| | | | | |
| Aerospace & Defense | Aerospace and Def... | 383835.0 | 26733.5 | 1010124 |
| | Apparel | 101157.3 | 6350.7 | 355699 |
| | Business Services | 23156.0 | 1667.4 | 127500 |
| | Diversified Outso... | 74175.0 | 5043.7 | 858600 |
| | Education | 6970.0 | 393.5 | 70653 |

We can target individual `fortune` columns for aggregation by using the same syntax as in section 9.5. Enter the column in square brackets after the `GroupBy` object; then invoke the aggregation method. The next example calculates the average revenue for companies within each sector/industry combo:

```
In [44] sector_and_industry[["Revenues"]].mean().head(5)

Out [44]
```

| Sector | Industry | |
|---------------------|----------------------------------|--------------|
| Aerospace & Defense | Aerospace and Defense | 15353.400000 |
| Apparel | Apparel | 7225.521429 |
| Business Services | Advertising, marketing | 11578.000000 |
| | Diversified Outsourcing Services | 5298.214286 |
| | Education | 3485.000000 |

Name: Revenues, dtype: float64

In summary, a `GroupBy` object is an optimal data structure for splitting, organizing, and aggregating a DataFrame's values. If you need to use multiple columns to identify buckets, pass the `groupby` method a list of columns.

9.7 Coding challenge

This coding challenge's data set, cereals.csv, is a listing of 80 popular breakfast cereals. Each row includes a cereal's name, manufacturer, type, calories, grams of fiber, and grams of sugar. Let's take a look:

```
In [45] cereals = pd.read_csv("cereals.csv")
       cereals.head()
```

```
Out [45]
```

| | Name | Manufacturer | Type | Calories | Fiber | Sugars |
|---|---------------------|----------------|------|----------|-------|--------|
| 0 | 100% Bran | Nabisco | Cold | 70 | 10.0 | 6 |
| 1 | 100% Natural Bran | Quaker Oats | Cold | 120 | 2.0 | 8 |
| 2 | All-Bran | Kellogg's | Cold | 70 | 9.0 | 5 |
| 3 | All-Bran with Ex... | Kellogg's | Cold | 50 | 14.0 | 0 |
| 4 | Almond Delight | Ralston Purina | Cold | 110 | 1.0 | 8 |

Good luck!

9.7.1 Problems

Here are the challenges:

- 1 Group the cereals, using the Manufacturer column's values.
- 2 Determine the total number of groups, and the number of cereals per group.
- 3 Extract the cereals that belong to the manufacturer/group "Nabisco".
- 4 Calculate the average of values in the Calories, Fiber, and Sugars columns for each manufacturer.
- 5 Find the maximum value in the Sugars column for each manufacturer.
- 6 Find the minimum value in the Fiber column for each manufacturer.
- 7 Extract the cereal with the lowest amount of grams of sugar per manufacturer in a new DataFrame.

9.7.2 Solutions

Let's dive into the solutions:

- 1 To group the cereals by manufacturer, we can invoke the `groupby` method on the cereals DataFrame and pass in the Manufacturer column. Pandas will use the column's unique values to organize the groups:

```
In [46] manufacturers = cereals.groupby("Manufacturer")
```

- 2 To find the total number of groups/manufacturers, we can pass the `GroupBy` object into Python's built-in `len` function:

```
In [47] len(manufacturers)
```

```
Out [47] 7
```

If you're curious, the `GroupBy` object's `size` method returns a `Series` with a count of cereals per group:

```
In [48] manufacturers.size()

Out [48] Manufacturer
          American Home Food Products      1
          General Mills                  22
          Kellogg's                      23
          Nabisco                        6
          Post                            9
          Quaker Oats                   8
          Ralston Purina                 8
          dtype: int64
```

- 3** To identify cereals belonging to the "Nabisco" group, we can invoke the `get_group` method on our `GroupBy` object. Pandas will return the nested `DataFrame` with "Nabisco" rows:

```
In [49] manufacturers.get_group("Nabisco")

Out [49]
```

| | Name | Manufacturer | Type | Calories | Fiber | Sugars |
|----|--------------------------|--------------|------|----------|-------|--------|
| 0 | 100% Bran | Nabisco | Cold | 70 | 10.0 | 6 |
| 20 | Cream of Wheat (Quick) | Nabisco | Hot | 100 | 1.0 | 0 |
| 63 | Shredded Wheat | Nabisco | Cold | 80 | 3.0 | 0 |
| 64 | Shredded Wheat 'n'Bran | Nabisco | Cold | 90 | 4.0 | 0 |
| 65 | Shredded Wheat spoon ... | Nabisco | Cold | 90 | 3.0 | 0 |
| 68 | Strawberry Fruit Wheats | Nabisco | Cold | 90 | 3.0 | 5 |

- 4** To calculate the averages of the numeric columns in `cereals`, we can invoke the `mean` method on the `manufacturers` `GroupBy` object. Pandas will aggregate all numeric columns in `cereals` by default:

```
In [50] manufacturers.mean()

Out [50]
```

| Manufacturer | Calories | Fiber | Sugars |
|-----------------------------|------------|----------|----------|
| American Home Food Products | 100.000000 | 0.000000 | 3.000000 |
| General Mills | 111.363636 | 1.272727 | 7.954545 |
| Kellogg's | 108.695652 | 2.739130 | 7.565217 |
| Nabisco | 86.666667 | 4.000000 | 1.833333 |
| Post | 108.888889 | 2.777778 | 8.777778 |
| Quaker Oats | 95.000000 | 1.337500 | 5.250000 |
| Ralston Purina | 115.000000 | 1.875000 | 6.125000 |

- 5** Next, we are tasked with finding the maximum Sugars value per manufacturer. We can use square brackets after a `GroupBy` object to identify which column's values to aggregate. Then we provide the correct aggregate method, which is `max` in this case:

```
In [51] manufacturers["Sugars"].max()

Out [51] Manufacturer
American Home Food Products      3
General Mills                     14
Kellogg's                          15
Nabisco                            6
Post                               15
Quaker Oats                        12
Ralston Purina                     11
Name: Sugars, dtype: int64
```

- 6 To find the smallest fiber value per manufacturer, we can swap the column to Fiber and invoke the min method:

```
In [52] manufacturers["Fiber"].min()
```

```
Out [52] Manufacturer
American Home Food Products      0.0
General Mills                     0.0
Kellogg's                          0.0
Nabisco                            1.0
Post                               0.0
Quaker Oats                        0.0
Ralston Purina                     0.0
Name: Fiber, dtype: float64
```

- 7 Finally, we need to identify the cereal row for each manufacturer with the lowest value in the Sugars column. We can solve this problem by using the apply method and a custom function. The smallest_sugar_row function uses the nsmallest method to pull the DataFrame row with the smallest value in the Sugars column. Then we use apply to invoke the custom function on each GroupBy group:

```
In [53] def smallest_sugar_row(df):
        return df.nsmallest(1, "Sugars")
```

```
In [54] manufacturers.apply(smallest_sugar_row)
```

```
Out [54]
```

| Manufacturer | | | Name | Manufacturer | Type | Calories | Fiber | Sugars |
|---------------------|----|--|--------------|---------------------|-------------|-----------------|--------------|---------------|
| American H... | 43 | | Maypo | American ... | Hot | 100 | 0.0 | 3 |
| General Mills | 11 | | Cheerios | General M... | Cold | 110 | 2.0 | 0 |
| Nabisco | 20 | | Cream of ... | Nabisco | Hot | 100 | 1.0 | 0 |
| Post | 33 | | Grape-Nuts | Post | Cold | 110 | 3.0 | 3 |
| Quaker Oats | 57 | | Quaker Oa... | Quaker Oats | Hot | 100 | 2.7 | -1 |
| Ralston Pu... | 61 | | Rice Chex | Ralston P... | Cold | 110 | 0.0 | 2 |

Congratulations on completing the coding challenge!

Summary

- A `GroupBy` object is a container of `DataFrames`.
- Pandas buckets rows into `GroupBy` `DataFrames` by using values across one or more columns.
- The `first` and `last` methods return the first and last rows from each `GroupBy` group. The row order in the original `DataFrame` determines the row order in each group.
- The `head` and `tail` methods extract multiple rows from each group in the `GroupBy` object based on the row's positions in the original `DataFrame`.
- The `nth` method extracts a row from each `GroupBy` group by its index position.
- Pandas can perform aggregate calculations such as sum, average, max, and min for each group in a `GroupBy` object.
- The `agg` method applies different aggregate operations to different columns. We pass it a dictionary with columns as keys and aggregation as values.
- The `apply` method invokes a function on each `DataFrame` in a `GroupBy` object.

10

Merging, joining, and concatenating

This chapter covers

- Concatenating `DataFrames` on the vertical and horizontal axes
- Merging `DataFrames` with inner joins, outer joins, and left joins
- Finding unique and shared values between `DataFrames`
- Joining `DataFrames` by index labels

As a business domain grows in complexity, it becomes increasingly difficult to store all data in a single collection. To solve this problem, data administrators split data across multiple tables. Then they associate the tables with one another so it is easy to identify the relationships among them.

You may have previously worked with a database such as PostgreSQL, MySQL, or Oracle. Relational database management systems (RDBMS) follow the paradigm described in the preceding paragraph. A database consists of tables. A table holds records for one domain model. A table consists of rows and columns. A row stores information for one record. A column stores an attribute for that record. Tables

connect through column keys. If you haven't worked with databases before, you can consider a table to be effectively equivalent to a pandas DataFrame.

Here's a real-world example. Imagine that we're building an e-commerce site and want to create a `users` table to store the website's registered users. Following relational database conventions, we would assign a unique numeric identifier to each record. We'll store the values in an `id` column. The `id` column's values are called *primary keys* because they are the primary identifiers for specific rows.

| Users | | | | |
|-------|------------|-----------|--------------------------|--------|
| id | first_name | last_name | email | gender |
| 1 | Homer | Simpson | donutfan@simpson.com | Male |
| 2 | Bart | Simpson | troublemaker@simpson.com | Male |

Let's imagine that our next goal is to keep track of users' orders on our site. We'll create an `orders` table to store order details such as item name and price. But how do we connect each order to the user who placed it? Take a peek at the following table:

| Orders | | | | |
|--------|-----------|-------|----------|---------|
| id | item | price | quantity | user_id |
| 1 | Donut Box | 4.99 | 4 | 1 |
| 2 | Slingshot | 19.99 | 1 | 2 |

To establish a relationship between two tables, database administrators create a column of foreign keys. A *foreign key* is a reference to a record in another table. It is labeled *foreign* because the key exists outside the current table's scope.

Each `orders` table row stores the ID of the *user* who placed the order in the `user_id` column. Thus, the `user_id` column stores foreign keys; its values are references to records in another table, the `users` table. Using the established relationship between the two tables, we can determine that order 1 was placed by the user with an `id` of 1, Homer Simpson.

The advantage of foreign keys is the reduction of data duplication. The `orders` table does not need to copy the user's first name, last name, and email for each order, for example. Rather, it needs only to store a single reference to the correct `users` record. The business entities of users and orders live separately, but we can connect them when necessary.

When it comes time to combine tables, we can always turn to pandas. The library excels at appending, concatenating, joining, merging, and combining DataFrames in both vertical and horizontal directions. It can identify unique and shared records between DataFrames. It can perform SQL operations such as inner joins, outer joins,

left joins, and right joins. In this chapter, we'll explore the differences among these joins and the situations in which each one can prove to be advantageous.

10.1 Introducing the data sets

Let's import the pandas library and assign it an alias of pd:

```
In [1] import pandas as pd
```

This chapter's data sets come from the online social service Meetup, a website where users join groups for common interests such as hiking, literature, and board games. Group organizers schedule remote or in-person events that group members attend. Meetup's domain has several data models, including groups, categories, and cities.

The meetup directory houses all data sets for this chapter. Let's begin our exploration by importing the groups1.csv and groups2.csv files. These files hold a sample of Meetup's registered groups. Each group includes an ID, name, associated category ID, and associated city ID. Here's what groups1 looks like:

```
In [2] groups1 = pd.read_csv("meetup/groups1.csv")
groups1.head()
```

```
Out [2]
```

| group_id | | name | category_id | city_id |
|----------|-------|-------------------------------|-------------|---------|
| 0 | 6388 | Alternative Health NYC | 14 | 10001 |
| 1 | 6510 | Alternative Energy Meetup | 4 | 10001 |
| 2 | 8458 | NYC Animal Rights | 26 | 10001 |
| 3 | 8940 | The New York City Anime Group | 29 | 10001 |
| 4 | 10104 | NYC Pit Bull Group | 26 | 10001 |

Let's also import groups2.csv. Notice that both CSVs have the same four columns. We can imagine that the groups data was somehow split and stored across two files instead of one:

```
In [3] groups2 = pd.read_csv("meetup/groups2.csv")
groups2.head()
```

```
Out [3]
```

| group_id | | name | category_id | city_id |
|----------|----------|--|-------------|---------|
| 0 | 18879327 | BachataMania | 5 | 10001 |
| 1 | 18880221 | Photoshoot Chicago - Photography and ... | 27 | 60601 |
| 2 | 18880426 | Chicago Adult Push / Kick Scooter Gro... | 31 | 60601 |
| 3 | 18880495 | Chicago International Soccer Club | 32 | 60601 |
| 4 | 18880695 | Impact.tech San Francisco Meetup | 2 | 94101 |

Each group has a category_id foreign key. We can find information on categories in the categories.csv file. Each row in this file stores the category's ID and name:

```
In [4] categories = pd.read_csv("meetup/categories.csv")
categories.head()
```

```
Out [4]
```

| | category_id | category_name |
|---|--------------------|-------------------------|
| 0 | 1 | Arts & Culture |
| 1 | 3 | Cars & Motorcycles |
| 2 | 4 | Community & Environment |
| 3 | 5 | Dancing |
| 4 | 6 | Education & Learning |

Each group also has a `city_id` foreign key. The `cities.csv` data set stores the city information. A city has a unique ID, name, state, and zip code. Let's take a look:

```
In [5] pd.read_csv("meetup/cities.csv").head()
```

```
Out [5]
```

| | id | city | state | zip |
|---|-----------|----------------|--------------|------------|
| 0 | 7093 | West New York | NJ | 7093 |
| 1 | 10001 | New York | NY | 10001 |
| 2 | 13417 | New York Mills | NY | 13417 |
| 3 | 46312 | East Chicago | IN | 46312 |
| 4 | 56567 | New York Mills | MN | 56567 |

The cities data set has a small issue. Look at the zip value in the first row. 7093 is an invalid zip code; the value in the CSV is in fact 07093. Zip codes can start with a leading zero. Unfortunately, pandas assumes that the zip codes are integers and thus strips the leading zeroes from the values. To solve this problem, we can add the `dtype` parameter to the `read_csv` function. `dtype` accepts a dictionary in which keys denote column names and values denote the data type to assign to that column. Let's make sure that pandas imports the zip column's values as strings:

```
In [6] cities = pd.read_csv(
    "meetup/cities.csv", dtype = {"zip": "string"}
)
cities.head()
```

```
Out [6]
```

| | id | city | state | zip |
|---|-----------|----------------|--------------|------------|
| 0 | 7093 | West New York | NJ | 07093 |
| 1 | 10001 | New York | NY | 10001 |
| 2 | 13417 | New York Mills | NY | 13417 |
| 3 | 46312 | East Chicago | IN | 46312 |
| 4 | 56567 | New York Mills | MN | 56567 |

Excellent; we're ready to proceed. To summarize, each group in `groups1` and `groups2` belongs to a category and a city. The `category_id` and `group_id` columns store foreign keys. The `category_id` column values map to the `category_id` column in `categories`. The `city_id` column values map to the `id` column in `cities`. With our data tables loaded into Jupyter, we're ready to start joining them.

10.2 Concatenating data sets

The simplest way to combine two data sets is with *concatenation*—appending one DataFrame to the end of another.

The `groups1` and `groups2` DataFrames both have the same four column names. Let's assume that they are two halves of a greater whole. We'd like to combine their rows into a single DataFrame. Pandas has a convenient `concat` function at the top level of the library. We can pass its `objs` parameter a list of DataFrames. Pandas will concatenate the objects in the order in which they appear in the `objs` list. The next example concatenates the rows in `groups2` to the end of `groups1`:

```
In [7] pd.concat(objs = [groups1, groups2])
```

```
Out [7]
```

| group_id | | name | category_id | city_id |
|----------|----------|--|-------------|---------|
| 0 | 6388 | Alternative Health NYC | 14 | 10001 |
| 1 | 6510 | Alternative Energy Meetup | 4 | 10001 |
| 2 | 8458 | NYC Animal Rights | 26 | 10001 |
| 3 | 8940 | The New York City Anime Group | 29 | 10001 |
| 4 | 10104 | NYC Pit Bull Group | 26 | 10001 |
| ... | ... | ... | ... | ... |
| 8326 | 26377464 | Shinect | 34 | 94101 |
| 8327 | 26377698 | The art of getting what you want [...] | 14 | 94101 |
| 8328 | 26378067 | Streeterville Running Group | 9 | 60601 |
| 8329 | 26378128 | Just Dance NYC | 23 | 10001 |
| 8330 | 26378470 | FREE Arabic Chicago Evanston North... | 31 | 60601 |

```
16330 rows × 4 columns
```

The concatenated DataFrame has 16,330 rows! As you might have guessed, its length is equal to the sum of the lengths of the `groups1` and `groups2` DataFrames:

```
In [8] len(groups1)
```

```
Out [8] 7999
```

```
In [9] len(groups2)
```

```
Out [9] 8331
```

```
In [10] len(groups1) + len(groups2)
```

```
Out [10] 16330
```

Pandas preserves the original index labels from both DataFrames in the concatenation, which is why we see a final index position of 8,330 in the concatenated DataFrame even though it has more than 16,000 rows. What we are seeing is the 8,330 index from the end of the `groups2` DataFrame. Pandas does not care that the same index number appears in both `groups1` and `groups2`. As a result, the concatenated index has duplicate index labels.

We can pass the concat function's ignore_index parameter an argument of True to generate pandas' standard numeric index. The concatenated DataFrame will discard the original index labels:

```
In [11] pd.concat(objs = [groups1, groups2], ignore_index = True)
```

```
Out [11]
```

| | group_id | | name | category_id | city_id |
|-------|------------------|--------------------------------------|------|-------------|---------|
| 0 | 6388 | Alternative Health NYC | 14 | 10001 | |
| 1 | 6510 | Alternative Energy Meetup | 4 | 10001 | |
| 2 | 8458 | NYC Animal Rights | 26 | 10001 | |
| 3 | 8940 | The New York City Anime Group | 29 | 10001 | |
| 4 | 10104 | NYC Pit Bull Group | 26 | 10001 | |
| ... | ... | ... | ... | ... | ... |
| 16325 | 26377464 | Shinect | 34 | 94101 | |
| 16326 | 26377698 | The art of getting what you want ... | 14 | 94101 | |
| 16327 | 26378067 | Streeterville Running Group | 9 | 60601 | |
| 16328 | 26378128 | Just Dance NYC | 23 | 10001 | |
| 16329 | 26378470 | FREE Arabic Chicago Evanston Nort... | 31 | 60601 | |
| 16330 | rows × 4 columns | | | | |

What if we wanted the best of both worlds: to create a nonduplicate index but also preserve which DataFrame each row of data came from? One solution is to add a keys parameter and pass it a list of strings. Pandas will associate each string in the keys list with the DataFrame at the same index position in the objs list. The keys and objs lists must be of equal length.

The next example assigns the groups1 DataFrame a key of "G1" and the groups2 DataFrame a key of "G2". The concat function returns a MultiIndex DataFrame. The MultiIndex's first level stores the keys, and its second level stores the index labels from the respective DataFrame:

```
In [12] pd.concat(objs = [groups1, groups2], keys = ["G1", "G2"])
```

```
Out [12]
```

| | group_id | | name | category_id | city_id |
|---------|----------|------------------------------------|------|-------------|---------|
| G1 0 | 6388 | Alternative Health NYC | 14 | 10001 | |
| 1 | 6510 | Alternative Energy Meetup | 4 | 10001 | |
| 2 | 8458 | NYC Animal Rights | 26 | 10001 | |
| 3 | 8940 | The New York City Anime Group | 29 | 10001 | |
| 4 | 10104 | NYC Pit Bull Group | 26 | 10001 | |
| ... | ... | ... | ... | ... | ... |
| G2 8326 | 26377464 | Shinect | 34 | 94101 | |
| 8327 | 26377698 | The art of getting what you wan... | 14 | 94101 | |
| 8328 | 26378067 | Streeterville Running Group | 9 | 60601 | |
| 8329 | 26378128 | Just Dance NYC | 23 | 10001 | |
| 8330 | 26378470 | FREE Arabic Chicago Evanston No... | 31 | 60601 | |

```
16330 rows × 4 columns
```

We can extract the original DataFrames by accessing the G1 or G2 keys on the first level of the MultiIndex. (See chapter 7 for a refresher on using the `loc` accessor on MultiIndex DataFrames.) Before we proceed, let's assign the concatenated DataFrame to a `groups` variable:

```
In [13] groups = pd.concat(objs = [groups1, groups2], ignore_index = True)
```

We'll come back to `groups` in section 10.4.

10.3 Missing values in concatenated DataFrames

When concatenating two DataFrames, pandas places NaNs at intersections of row labels and column labels that the data sets do not share. Consider the following two DataFrames, both of which have a Football column. The `sports_champions_A` DataFrame has an exclusive Baseball column, and the `sports_champions_B` DataFrame has an exclusive Hockey column:

```
In [14] sports_champions_A = pd.DataFrame(
    data = [
        ["New England Patriots", "Houston Astros"],
        ["Philadelphia Eagles", "Boston Red Sox"]
    ],
    columns = ["Football", "Baseball"],
    index = [2017, 2018]
)

sports_champions_A
```

```
Out [14]
```

| | Football | Baseball |
|------|----------------------|-----------------|
| 2017 | New England Patriots | Houston Astros |
| 2018 | Philadelphia Eagles | Boston Red Sox |

```
In [15] sports_champions_B = pd.DataFrame(
    data = [
        ["New England Patriots", "St. Louis Blues"],
        ["Kansas City Chiefs", "Tampa Bay Lightning"]
    ],
    columns = ["Football", "Hockey"],
    index = [2019, 2020]
)

sports_champions_B
```

```
Out [15]
```

| | Football | Hockey |
|------|----------------------|---------------------|
| 2019 | New England Patriots | St. Louis Blues |
| 2020 | Kansas City Chiefs | Tampa Bay Lightning |

If we concatenate the DataFrames, we will create missing values in the Baseball and Hockey columns. The sports_champions_A DataFrame has no values to place in the Hockey column, and the sports_champions_B DataFrame has no values to place in the Baseball column:

```
In [16] pd.concat(objs = [sports_champions_A, sports_champions_B])
```

```
Out [16]
```

| | Football | Baseball | Hockey |
|------|----------------------|-----------------|---------------------|
| 2017 | New England Patriots | Houston Astros | NaN |
| 2018 | Philadelphia Eagles | Boston Red Sox | NaN |
| 2019 | New England Patriots | NaN | St. Louis Blues |
| 2020 | Kansas City Chiefs | NaN | Tampa Bay Lightning |

By default, pandas concatenates rows on the horizontal axis. Sometimes, we want to append the rows on the vertical axis instead. Consider the sports_champions_C DataFrame, which has the same two index labels as sports_champions_A (2017 and 2018) but two different columns, Hockey and Basketball:

```
In [17] sports_champions_C = pd.DataFrame(
    data = [
        ["Pittsburgh Penguins", "Golden State Warriors"],
        ["Washington Capitals", "Golden State Warriors"]
    ],
    columns = ["Hockey", "Basketball"],
    index = [2017, 2018]
)

sports_champions_C
```

```
Out [17]
```

| | Hockey | Basketball |
|------|---------------------|-----------------------|
| 2017 | Pittsburgh Penguins | Golden State Warriors |
| 2018 | Washington Capitals | Golden State Warriors |

When we concatenate sports_champions_A and sports_champions_C, pandas appends the rows of the second DataFrame to the end of the first. The process creates duplicate 2017 and 2018 index labels:

```
In [18] pd.concat(objs = [sports_champions_A, sports_champions_C])
```

```
Out [18]
```

| | Football | Baseball | Hockey | Basketball |
|------|------------------|-----------------|------------------|-------------------|
| 2017 | New England P... | Houston Astros | NaN | NaN |
| 2018 | Philadelphia ... | Boston Red Sox | NaN | NaN |
| 2017 | NaN | NaN | Pittsburgh Pe... | Golden State ... |
| 2018 | NaN | NaN | Washington Ca... | Golden State ... |

This result is not what we want. Rather, we'd like to align the duplicate index labels (2017 and 2018) so that the columns have no missing values.

The concat function includes an axis parameter. We can pass that parameter an argument of either 1 or "columns" to concatenate the DataFrames across the column axis:

```
In [19] # The two lines below are equivalent
pd.concat(
    objs = [sports_champions_A, sports_champions_C],
    axis = 1
)
pd.concat(
    objs = [sports_champions_A, sports_champions_C],
    axis = "columns"
)

Out [19]
```

| | Football | Baseball | Hockey | Basketball |
|------|------------------|-----------------|------------------|-------------------|
| 2017 | New England P... | Houston Astros | Pittsburgh Pe... | Golden State ... |
| 2018 | Philadelphia ... | Boston Red Sox | Washington Ca... | Golden State ... |

Much better!

In summary, the concat function combines two DataFrames by appending one to the end of the other on either the horizontal axis or the vertical axis. I like to describe the process as "gluing" two data sets together.

10.4 Left joins

Compared with a concatenation, a *join* uses a logical criterion to determine which rows or columns to merge between two data sets. A join can target only rows with shared values between both data sets, for example. The following sections cover three types of joins: left, inner, and outer. Let's walk through them one by one.

A *left join* uses keys from one data set to pull in values from another. It is equivalent to a VLOOKUP operation in Excel. A left join is optimal when one data set is the focal point of the analysis. We pull in the second data set to provide supplemental information related to the primary data set. Consider the diagram in figure 10.1. Think of each circle as being a DataFrame. The DataFrame on the left is the focus of the analysis.

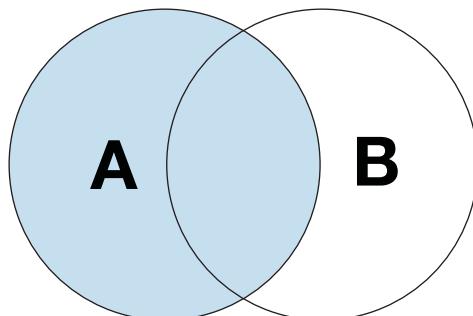


Figure 10.1 Left join diagram

Here's a quick reminder of what our groups data set looks like:

```
In [20] groups.head(3)
```

```
Out [20]
```

| group_id | name | category_id | city_id |
|----------|---------------------------|-------------|---------|
| 0 | Alternative Health NYC | 14 | 10001 |
| 1 | Alternative Energy Meetup | 4 | 10001 |
| 2 | NYC Animal Rights | 26 | 10001 |

The foreign keys in the category_id column reference the IDs in the categories data set:

```
In [21] categories.head(3)
```

```
Out [21]
```

| category_id | category_name |
|-------------|-------------------------|
| 0 | Arts & Culture |
| 1 | Cars & Motorcycles |
| 2 | Community & Environment |

Let's execute a left join on groups to add category information for each group. We'll use the `merge` method to merge one DataFrame into another. The method's first parameter, `right`, accepts a DataFrame. The terminology comes from the previous diagram. The right DataFrame is the circle on the right, the "second" data set. We can pass a string denoting the type of join to the method's `how` parameter; we'll pass in "`left`". We also must tell pandas which columns to use to match values between the two DataFrames. Let's add an `on` parameter with a value of "`category_id`". We can use the `on` parameter only when the column name is equal between DataFrames. In our case, both the groups and categories DataFrames have a `category_id` column:

```
In [22] groups.merge(categories, how = "left", on = "category_id").head()
```

```
Out [22]
```

| group_id | name | category_id | city_id | category_name |
|----------|---------------------|-------------|---------|---------------------|
| 0 | Alternative Heal... | 14 | 10001 | Health & Wellbeing |
| 1 | Alternative Ener... | 4 | 10001 | Community & Envi... |
| 2 | NYC Animal Rights | 26 | 10001 | NaN |
| 3 | The New York Cit... | 29 | 10001 | Sci-Fi & Fantasy |
| 4 | NYC Pit Bull Group | 26 | 10001 | NaN |

There it is! Pandas pulls in the categories table's columns whenever it finds a match for the `category_id` value in `groups`. The one exception is the `category_id` column, which is listed only once. Note that when the library does not find a `category_id` in `categories`, it displays `NaN` values in the `category_name` column from `categories`. We can see an example on rows 2 and 4 of the previous output.

10.5 Inner joins

An *inner join* targets values that exist across two DataFrames. Consider figure 10.2; an inner join targets the colored overlap in the middle of the circles.

In an inner join, pandas excludes values that exist only in the first DataFrame and only in the second DataFrame.

Here's a reminder of what the groups and categories data sets look like:

```
In [23] groups.head(3)
```

```
Out [23]
```

| group_id | name | category_id | city_id |
|----------|--------------------------------|-------------|---------|
| 0 | 6388 Alternative Health NYC | 14 | 10001 |
| 1 | 6510 Alternative Energy Meetup | 4 | 10001 |
| 2 | 8458 NYC Animal Rights | 26 | 10001 |

```
In [24] categories.head(3)
```

```
Out [24]
```

| category_id | category_name |
|-------------|-------------------------|
| 0 | Arts & Culture |
| 1 | Cars & Motorcycles |
| 2 | Community & Environment |

Let's identify the categories that exist in both data sets. From a technical perspective, we once again want to target the rows from the two DataFrames with equal values in the category_id columns. In this situation, it doesn't matter whether we invoke the merge method on group or categories. An inner join identifies common elements in both data sets; the results will be the same regardless. For the next example, let's call the merge method on groups:

```
In [25] groups.merge(categories, how = "inner", on = "category_id")
```

```
Out [25]
```

| group_id | name | category_id | city_id | category_name |
|----------|--------------------------|-------------|---------|-------------------|
| 0 | 6388 Alternative He... | 14 | 10001 | Health & Wellb... |
| 1 | 54126 Energy Healers... | 14 | 10001 | Health & Wellb... |
| 2 | 67776 Flourishing Li... | 14 | 10001 | Health & Wellb... |
| 3 | 111855 Hypnosis & NLP... | 14 | 10001 | Health & Wellb... |
| 4 | 129277 The Live Food ... | 14 | 60601 | Health & Wellb... |
| ... | ... | ... | ... | ... |

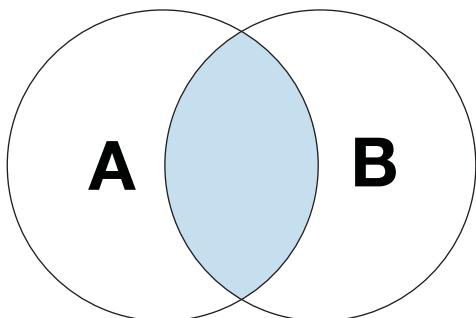


Figure 10.2 Inner join diagram

```

8032 25536270 New York Cucko...      17    10001      Lifestyle
8033 25795045 Pagans Paradis...     17    10001      Lifestyle
8034 25856573 Fuck Yeah Femm...     17    94101      Lifestyle
8035 26158102 Chicago Crossd...     17    60601      Lifestyle
8036 26219043 Corporate Goes...     17    10001      Lifestyle

```

8037 rows × 5 columns

The merged DataFrame includes all columns from both the groups and categories DataFrames. The values in the category_id column appear in both groups and categories. The category_id column is listed only once. We don't need a duplicate column because the values in category_id are the same for groups and categories in an inner join.

Let's add some context to what pandas did. The first four rows in the merged DataFrame have a category_id of 14. We can filter for that ID in the groups and categories DataFrames:

In [26] groups[groups["category_id"] == 14]

Out [26]

| group_id | name | category_id | city_id |
|----------|--------------------------------------|-------------|---------|
| 0 | Alternative Health NYC | 14 | 10001 |
| 52 | Energy Healers NYC | 14 | 10001 |
| 78 | Flourishing Life Meetup | 14 | 10001 |
| 121 | Hypnosis & NLP NYC - Update Your ... | 14 | 10001 |
| 136 | The Live Food Chicago Community | 14 | 60601 |
| ... | ... | ... | ... |
| 16174 | The Transformation Project: Colla... | 14 | 94101 |
| 16201 | Cognitive Empathy, How To Transla... | 14 | 10001 |
| 16248 | Contemplative Practices Group | 14 | 94101 |
| 16314 | The art of getting what you want:... | 14 | 94101 |
| 16326 | The art of getting what you want ... | 14 | 94101 |

870 rows × 4 columns

In [27] categories[categories["category_id"] == 14]

Out [27]

| category_id | category_name |
|-------------|--------------------|
| 8 | Health & Wellbeing |

The merged DataFrame creates one row for each group_id match across the two DataFrames. There are 870 rows in groups and one row in categories with a group_id of 14. Pandas pairs each of the 870 rows in groups with the single row in categories and creates a total of 870 rows in the merged DataFrame. Because an inner join creates a new row for each value match, the merged DataFrame can be significantly larger than the original ones. If there were three categories with an ID of 14, for example, pandas would create 2610 rows (870 × 3).

10.6 Outer joins

An *outer join* combines all records across two data sets. Exclusivity does not matter with an outer join. Figure 10.3 shows the results of an outer join; pandas includes all values irrespective of whether they belong in one data set or both data sets.

Here's a reminder of what the groups and cities DataFrames look like:

```
In [28] groups.head(3)
```

```
Out [28]
```

| | group_id | | | | name | category_id | city_id |
|---|----------|--------------------|--------|--|------|-------------|---------|
| 0 | 6388 | Alternative Health | NYC | | | 14 | 10001 |
| 1 | 6510 | Alternative Energy | Meetup | | | 4 | 10001 |
| 2 | 8458 | NYC Animal Rights | | | | 26 | 10001 |

```
In [29] cities.head(3)
```

```
Out [29]
```

| | id | city | state | zip |
|---|-------|----------------|-------|-------|
| 0 | 7093 | West New York | NJ | 07093 |
| 1 | 10001 | New York | NY | 10001 |
| 2 | 13417 | New York Mills | NY | 13417 |

Let's merge groups and cities with an outer join. We'll pull in all cities: the ones exclusive to groups, the ones exclusive to cities, and the ones common to both.

So far, we've used only shared column names to merge data sets. When column names differ between data sets, we must pass different parameters to the `merge` method. Instead of the `on` parameter, we can use the `merge` method's `left_on` and `right_on` parameters. We pass `left_on` the column name in the left DataFrame and `right_on` the column name in the right DataFrame. Here, we perform an outer join to merge city information from cities into the groups DataFrame:

```
In [30] groups.merge(
    cities, how = "outer", left_on = "city_id", right_on = "id"
)
```

```
Out [30]
```

| | group_id | name | category_id | city_id | city | state | zip |
|---|----------|-----------|-------------|---------|----------|-------|-------|
| 0 | 6388.0 | Altern... | 14.0 | 10001.0 | New York | NY | 10001 |
| 1 | 6510.0 | Altern... | 4.0 | 10001.0 | New York | NY | 10001 |
| 2 | 8458.0 | NYC An... | 26.0 | 10001.0 | New York | NY | 10001 |
| 3 | 8940.0 | The Ne... | 29.0 | 10001.0 | New York | NY | 10001 |
| 4 | 10104.0 | NYC Pi... | 26.0 | 10001.0 | New York | NY | 10001 |
| | ... | ... | ... | ... | ... | ... | ... |

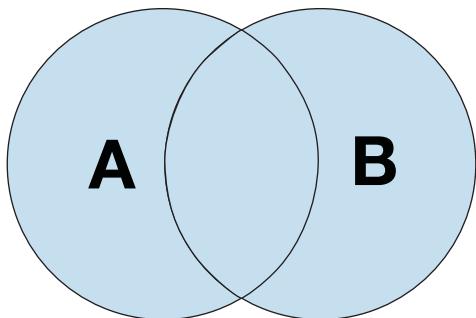


Figure 10.3 Outer join diagram

```

16329    243034... Midwes...
16330        NaN      NaN      NaN      NaN  New Yo...
16331        NaN      NaN      NaN      NaN  East C...
16332        NaN      NaN      NaN      NaN  New Yo...
16333        NaN      NaN      NaN      NaN  Chicag...

```

16334 rows × 8 columns

The final DataFrame has all city IDs from both data sets. If pandas finds a values match between the city_id and id columns, it merges the columns from the two DataFrames in a single row. We can see some examples in the first five rows. The city_id column stores the common id.

If one DataFrame has a value that the other does not, pandas places a `NaN` value in the city_id column. We can see some examples at the end of the data set. This placement will happen irrespective of whether groups or cities has the exclusive value.

We can pass `True` to the `merge` method's `indicator` parameter to identify which DataFrame a value belongs to. The merged DataFrame will include a `_merge` column that stores the values "both", "left_only", and "right_only":

```

In [31] groups.merge(
        cities,
        how = "outer",
        left_on = "city_id",
        right_on = "id",
        indicator = True
    )

Out [31]

```

| | <code>group_id</code> | <code>name</code> | <code>category_id</code> | <code>city_id</code> | <code>city</code> | <code>state</code> | <code>zip</code> | <code>_merge</code> |
|-------|-----------------------|-------------------|--------------------------|----------------------|-------------------|--------------------|------------------|---------------------|
| 0 | 6388.0 | Alt... | 14.0 | 100... | New... | NY | 10001 | both |
| 1 | 6510.0 | Alt... | 4.0 | 100... | New... | NY | 10001 | both |
| 2 | 8458.0 | NYC... | 26.0 | 100... | New... | NY | 10001 | both |
| 3 | 8940.0 | The... | 29.0 | 100... | New... | NY | 10001 | both |
| 4 | 101... | NYC... | 26.0 | 100... | New... | NY | 10001 | both |
| ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 16329 | 243... | Mid... | 34.0 | 600... | Nor... | IL | 60064 | both |
| 16330 | NaN | NaN | NaN | NaN | New... | NY | 13417 | rig... |
| 16331 | NaN | NaN | NaN | NaN | Eas... | IN | 46312 | rig... |
| 16332 | NaN | NaN | NaN | NaN | New... | MN | 56567 | rig... |
| 16333 | NaN | NaN | NaN | NaN | Chi... | CA | 95712 | rig... |

16334 rows × 9 columns

We can use the `_merge` column to filter rows that belong to either of the DataFrames. The next example extracts rows with a value of "right_only" in the `_merge` column or, equivalently, the city IDs that are present only in cities, the right DataFrame:

```

In [32] outer_join = groups.merge(
        cities,
        how = "outer",
        left_on = "city_id",
        right_on = "id",
        indicator = True
    )

```

```

in_right_only = outer_join["_merge"] == "right_only"
outer_join[in_right_only].head()

Out [32]

```

| | group_id | name | category_id | city_id | city | state | zip | _merge |
|-------|----------|------|-------------|---------|------|----------|-----|--------|
| 16330 | | NaN | NaN | NaN | NaN | New Y... | NY | 13417 |
| 16331 | | NaN | NaN | NaN | NaN | East ... | IN | 46312 |
| 16332 | | NaN | NaN | NaN | NaN | New Y... | MN | 56567 |
| 16333 | | NaN | NaN | NaN | NaN | Chica... | CA | 95712 |

With a few lines of code, we can easily filter out exclusive values in each data set.

10.7 Merging on index labels

Imagine that a DataFrame we'd like to join stores its primary keys in its index. Let's simulate this scenario. We can invoke the `set_index` method on cities to set its id column as its DataFrame index:

```

In [33] cities.head(3)

Out [33]

```

| | id | city | state | zip |
|---|-------|----------------|-------|-------|
| 0 | 7093 | West New York | NJ | 07093 |
| 1 | 10001 | New York | NY | 10001 |
| 2 | 13417 | New York Mills | NY | 13417 |

```

In [34] cities = cities.set_index("id")

In [35] cities.head(3)

Out [35]

```

| | city | state | zip |
|-------|----------------|-------|-------|
| id | | | |
| 7093 | West New York | NJ | 07093 |
| 10001 | New York | NY | 10001 |
| 13417 | New York Mills | NY | 13417 |

Let's use a left join to merge cities into groups again. Here's a quick reminder of what groups looks like:

```

In [36] groups.head(3)

Out [36]

```

| | group_id | name | category_id | city_id |
|---|----------|---------------------------|-------------|---------|
| 0 | 6388 | Alternative Health NYC | 14 | 10001 |
| 1 | 6510 | Alternative Energy Meetup | 4 | 10001 |
| 2 | 8458 | NYC Animal Rights | 26 | 10001 |

Now we want to compare the values in the `city_id` column in groups with the index labels of cities. When we invoke the `merge` method, we'll pass the `how` parameter an argument of `"left"` for a left join. We'll use the `left_on` parameter to tell pandas to

look for matches in the `city_id` column in groups, the left DataFrame. To look for matches in the index of the right DataFrame, we can provide a different parameter, `right_index`, and set it to True. The argument tells pandas to look for `city_id` matches in the right DataFrame's index:

```
In [37] groups.merge(
    cities,
    how = "left",
    left_on = "city_id",
    right_index = True
)
```

```
Out [37]
```

| <code>group_id</code> | <code>name</code> | <code>category_id</code> | <code>city_id</code> | <code>city</code> | <code>state</code> | <code>zip</code> |
|-----------------------|-------------------|--------------------------|----------------------|-------------------|--------------------|------------------|
| 0 | 6388 | Alterna... | 14 | 10001 | New York | NY 10001 |
| 1 | 6510 | Alterna... | 4 | 10001 | New York | NY 10001 |
| 2 | 8458 | NYC Ani... | 26 | 10001 | New York | NY 10001 |
| 3 | 8940 | The New... | 29 | 10001 | New York | NY 10001 |
| 4 | 10104 | NYC Pit... | 26 | 10001 | New York | NY 10001 |
| ... | ... | ... | ... | ... | ... | ... |
| 16325 | 26377464 | Shinect | 34 | 94101 | San Fra... | CA 94101 |
| 16326 | 26377698 | The art... | 14 | 94101 | San Fra... | CA 94101 |
| 16327 | 26378067 | Streete... | 9 | 60601 | Chicago | IL 60290 |
| 16328 | 26378128 | Just Da... | 23 | 10001 | New York | NY 10001 |
| 16329 | 26378470 | FREE Ar... | 31 | 60601 | Chicago | IL 60290 |

16330 rows × 7 columns

The method also supports a complementary `left_index` parameter. Pass that parameter an argument of True to tell pandas to look for matches in the left DataFrame's index. The left DataFrame is the one that we invoke the `merge` method on.

10.8 Coding challenge

We've reached the end of our exploration; thanks for joining us (pun intended)! Let's practice the concepts introduced in this chapter.

This coding challenge's tables summarize sales in a fictional restaurant. The `week_1_sales.csv` and `week_2_sales.csv` files hold listings of weekly transactions. Each restaurant order includes the ID of a customer who placed an order and the ID of the food item they purchased. Here's a preview of the first five rows of `week_1_sales`:

```
In [38] pd.read_csv("restaurant/week_1_sales.csv").head()
```

```
Out [38]
```

| <code>Customer ID</code> | <code>Food ID</code> |
|--------------------------|----------------------|
| 0 | 537 |
| 1 | 97 |
| 2 | 658 |
| 3 | 202 |
| 4 | 155 |

The week_2_sales data set has an identical shape. Let's import the two CSVs and assign them to week1 and week2 variables:

```
In [39] week1 = pd.read_csv("restaurant/week_1_sales.csv")
       week2 = pd.read_csv("restaurant/week_2_sales.csv")
```

The Customer ID columns hold foreign keys that reference values in the ID column in customers.csv. Each record in customers.csv includes a customer's first name, last name, gender, company, and occupation. Let's import that data set with the `read_csv` function and set its ID column as the DataFrame index with the `index_col` parameter:

```
In [40] pd.read_csv("restaurant/customers.csv", index_col = "ID").head()
```

```
Out [40]
```

| ID | First Name | Last Name | Gender | Company | Occupation |
|----|------------|-----------|--------|---------|-------------------------------|
| 1 | Joseph | Perkins | Male | Dynazzy | Community Outreach Specialist |
| 2 | Jennifer | Alvarez | Female | DabZ | Senior Quality Engineer |
| 3 | Roger | Black | Male | Tagfeed | Account Executive |
| 4 | Steven | Evans | Male | Fatz | Registered Nurse |
| 5 | Judy | Morrison | Female | Demivee | Legal Assistant |

```
In [41] customers = pd.read_csv(
           "restaurant/customers.csv", index_col = "ID"
         )
```

There's another column of foreign keys in the weeks1 and weeks2 DataFrames. The Food ID foreign key connects to the ID column in foods.csv. A food item includes an ID, a name, and a price. When we import this data set, let's set its Food ID column as the DataFrame index:

```
In [42] pd.read_csv("restaurant/foods.csv", index_col = "Food ID")
```

```
Out [42]
```

| Food ID | Food Item | Price |
|---------|------------|-------|
| 1 | Sushi | 3.99 |
| 2 | Burrito | 9.99 |
| 3 | Taco | 2.99 |
| 4 | Quesadilla | 4.25 |
| 5 | Pizza | 2.49 |
| 6 | Pasta | 13.99 |
| 7 | Steak | 24.99 |
| 8 | Salad | 11.25 |
| 9 | Donut | 0.99 |
| 10 | Drink | 1.75 |

```
In [43] foods = pd.read_csv("restaurant/foods.csv", index_col = "Food ID")
```

With the data sets imported, we're ready to tackle the exercises.

10.8.1 Problems

Here are the challenges:

- 1 Concatenate the two weeks of sales data into one DataFrame. Assign the week1 DataFrame a key of "Week 1" and the week2 DataFrame a key of "Week 2".
- 2 Find the customers who ate at the restaurant both weeks.
- 3 Find the customers who ate at the restaurant both weeks and ordered the same item each week.

HINT You can join data sets on multiple columns by passing the `on` parameter a list of columns.

- 4 Identify which customers came in only on Week 1 and only on Week 2.
- 5 Each row in the week1 DataFrame identifies a customer who purchased a food item. For each row, pull in the customer's information from the customers DataFrame.

10.8.2 Solutions

Let's explore the solutions:

- 1 Our first challenge is to combine the two weeks of restaurant sales data into a single DataFrame. The `concat` function at the top level of pandas offers a perfect solution. We can pass the two DataFrames in a list to the function's `objs` parameter. To assign a MultiIndex level to each DataFrame in the result, we'll also provide the `keys` parameter a list with the level labels:

```
In [44] pd.concat(objs = [week1, week2], keys = ["Week 1", "Week 2"])

Out [44]
```

| | Customer ID | Food ID |
|---------------|-------------|---------|
| Week 1 | 0 | 537 |
| | 1 | 97 |
| | 2 | 658 |
| | 3 | 202 |
| | 4 | 155 |
| ... | | ... |
| Week 2 | 245 | 783 |
| | 246 | 556 |
| | 247 | 547 |
| | 248 | 252 |
| | 249 | 249 |

500 rows × 2 columns

- 2 Next, we want to identify customers who visited the restaurant both weeks. From a technical perspective, we need to find the Customer IDs present in both the week1 and week2 DataFrames. An inner join is what we're looking for here. Let's invoke the `merge` method on week1 and pass in week2 as the right DataFrame. We'll declare the join type as "inner" and tell pandas to look for shared values in the Customer ID columns:

```
In [45] week1.merge(
    right = week2, how = "inner", on = "Customer ID"
).head()
```

Out [45]

| | Customer ID | Food ID_x | Food ID_y |
|---|-------------|-----------|-----------|
| 0 | 537 | 9 | 5 |
| 1 | 155 | 9 | 3 |
| 2 | 155 | 1 | 3 |
| 3 | 503 | 5 | 8 |
| 4 | 503 | 5 | 9 |

Remember that the inner join shows all matches of customer IDs across the week1 and week2 DataFrames. Thus, there are duplicates in the result (customers 155 and 503). If we wanted to remove duplicates, we could invoke the drop_duplicates method introduced in chapter 5:

```
In [46] week1.merge(
    right = week2, how = "inner", on = "Customer ID"
).drop_duplicates(subset = ["Customer ID"]).head()
```

Out [46]

| | Customer ID | Food ID_x | Food ID_y |
|---|-------------|-----------|-----------|
| 0 | 537 | 9 | 5 |
| 1 | 155 | 9 | 3 |
| 3 | 503 | 5 | 8 |
| 5 | 550 | 6 | 7 |
| 6 | 101 | 7 | 4 |

- 3 The third challenge asks to find the customers who visited the restaurant both weeks and ordered the same item. Once again, an inner join is the right option for finding values present in both the left and right DataFrames. This time around, however, we have to pass the on parameter a list with two columns. The values in both the Customer ID and Food ID columns must match between week1 and week2:

```
In [47] week1.merge(
    right = week2,
    how = "inner",
    on = ["Customer ID", "Food ID"]
)
```

Out [47]

| | Customer ID | Food ID |
|---|-------------|---------|
| 0 | 304 | 3 |
| 1 | 540 | 3 |
| 2 | 937 | 10 |
| 3 | 233 | 3 |
| 4 | 21 | 4 |
| 5 | 21 | 4 |
| 6 | 922 | 1 |
| 7 | 578 | 5 |
| 8 | 578 | 5s |

- 4 One solution to identify the customers who came in only one week is to use an outer join. We can match records across the two DataFrames by using values in the Customer ID column. Let's pass the indicator parameter a value of True to add a _merge column. Pandas will indicate whether the Customer ID exists in only the left table ("left_only"), only the right table ("right_only"), or both tables ("both"):

```
In [48] week1.merge(
    right = week2,
    how = "outer",
    on = "Customer ID",
    indicator = True
).head()
```

Out [48]

| | Customer ID | Food ID_x | Food ID_y | _merge |
|---|-------------|-----------|-----------|-----------|
| 0 | 537 | 9.0 | 5.0 | both |
| 1 | 97 | 4.0 | NaN | left_only |
| 2 | 658 | 1.0 | NaN | left_only |
| 3 | 202 | 2.0 | NaN | left_only |
| 4 | 155 | 9.0 | 3.0 | both |

- 5 The final challenge asks to pull customer information into the week1 table. A left join is an optimal solution. Invoke the merge method on the week1 DataFrame, passing in the customers DataFrame as the right data set. Pass the how parameter an argument of "left".

The tricky part of this challenge is that the week1 DataFrame stores the customer IDs in its Customer ID column, whereas the customers DataFrame stores them in its index labels. To solve the problem, we can pass the left_on parameter the column name from the week1 DataFrame and the right_index parameter a value of True:

```
In [49] week1.merge(
    right = customers,
    how = "left",
    left_on = "Customer ID",
    right_index = True
).head()
```

Out [49]

| | Customer ID | Food ID | First Name | Last Name | Gender | Company | Occupation |
|---|-------------|---------|------------|-----------|--------|-----------|------------|
| 0 | 537 | 9 | Cheryl | Carroll | Female | Zoombeat | Regist... |
| 1 | 97 | 4 | Amanda | Watkins | Female | Ozu | Accoun... |
| 2 | 658 | 1 | Patrick | Webb | Male | Browsebug | Commun... |
| 3 | 202 | 2 | Louis | Campbell | Male | Rhynoodle | Accoun... |
| 4 | 155 | 9 | Carolyn | Diaz | Female | Gigazoom | Databa... |

Congratulations on completing the coding challenge!

Summary

- A *primary key* is a unique identifier for a record in a data set.
- A *foreign key* is a reference to a record in another data set.
- The `concat` function concatenates DataFrames on either the horizontal or vertical axis.
- The `merge` method joins two DataFrames based on some logical criterion.
- An *inner join* identifies common values between two DataFrames. For any matches, pandas pulls all columns from the right DataFrame into the left DataFrame.
- An *outer join* merges two DataFrames. Pandas includes values whether they are exclusive to one data set or shared.
- A *left join* pulls in columns from the right DataFrame when their values exist in the left DataFrame. The operation is equivalent to a VLOOKUP in Excel.
- A left join is ideal when the second DataFrame contains supplemental information that we'd like to attach to the primary DataFrame.

11

Working with dates and times

This chapter covers

- Converting Series of strings to datetimes
- Retrieving date and time information from datetime objects
- Rounding dates to week, month, and quarter ends
- Adding and subtracting datetimes to and from each other

A *datetime* is a data type for storing date and time. It can model a specific date (such as October 4, 2021), a particular time (such as 11:50 a.m.), or both (such as October 4, 2021 at 11:50 a.m.). Datetimes are valuable because they allow us to track trends over time. A financial analyst may use datetimes to determine the weekdays when a stock performs best. A restaurant owner may use them to discover the peak hours that customers are patronizing the business. An operations manager may use them to identify the parts of a process that are creating bottlenecks in production. The *when* in a data set can often lead to the *why*.

In this chapter, we'll review Python's built-in datetime objects and see how pandas improves them with its `Timestamp` and `Timedelta` objects. We'll also learn

how to use the library to convert strings to dates, add and subtract offsets of time, calculate durations, and more. There's no time to waste (pun intended), so let's dive in.

11.1 Introducing the *Timestamp* object

A *module* is a file with Python code. Python's standard library is a collection of more than 250 modules baked into the language that provide battle-tested solutions to common problems such as database connections, mathematics, and testing. The standard library exists so developers can write software that uses core language features rather than install additional dependencies. It's often said that Python comes with "batteries included"; like a toy, the language is ready to be used out of the box.

11.1.1 How Python works with *datetimes*

To reduce memory consumption, Python does not autoload its standard library modules by default. Instead, we must explicitly import any desired modules into our project. As with an external package (such as pandas), we can import a module with the `import` keyword and assign it an alias with the `as` keyword. The standard library's `datetime` module is our target; it stores classes for working with dates and times. `dt` is a popular alias for the `datetime` module. Let's spin up a fresh Jupyter Notebook and import `datetime` along with the `pandas` library:

```
In [1] import datetime as dt  
      import pandas as pd
```

Let's review four classes in the module: `date`, `time`, `datetime`, and `timedelta`. (See appendix B for more details on classes and objects.)

A `date` models a single day in history. The object does not store any time. The `date` class constructor accepts sequential `year`, `month`, and `day` parameters. All parameters expect integers. The next example instantiates a `date` object for my birthday, April 12, 1991:

```
In [2] # The two lines below are equivalent  
      birthday = dt.date(1991, 4, 12)  
      birthday = dt.date(year = 1991, month = 4, day = 12)  
      birthday  
  
Out [2] datetime.date(1991, 4, 12)
```

The `date` object saves the constructor's arguments as object attributes. We can access their values with the `year`, `month`, and `day` attributes:

```
In [3] birthday.year  
Out [3] 1991  
  
In [4] birthday.month  
Out [4] 4
```

```
In [5] birthday.day
```

```
Out [5] 12
```

A date object is *immutable*—we cannot change its internal state after we create it. Python will raise an `AttributeError` exception if we attempt to overwrite any date attributes:

```
In [6] birthday.month = 10
```

```
-----
AttributeError                                 Traceback (most recent call last)
<ipython-input-15-2690a31d7b19> in <module>
----> 1 birthday.month = 10
```

```
AttributeError: attribute 'month' of 'datetime.date' objects is not writable
```

The complementary `time` class models a specific time of day. The date is irrelevant. The `time` constructor's first three parameters accept integer arguments for hour, minute, and second. Like a `date` object, a `time` object is immutable. The next example instantiates a `time` object modeling 6:43:25 a.m.:

```
In [7] # The two lines below are equivalent
alarm_clock = dt.time(6, 43, 25)
alarm_clock = dt.time(hour = 6, minute = 43, second = 25)
alarm_clock
```

```
Out [7] datetime.time(6, 43, 25)
```

The default argument for all three parameters is 0. If we instantiate a `time` object without arguments, it will represent midnight (12:00:00 a.m.). Midnight is 0 hours, 0 minutes, and 0 seconds into the day:

```
In [8] dt.time()
```

```
Out [8] datetime.time(0, 0)
```

The next example passes in 9 for the `hour` parameter, 42 for the `second` parameter, and no value for the `minute` parameter. The `time` object substitutes 0 for the `minutes` value. The resulting time is 9:00:42 a.m.:

```
In [9] dt.time(hour = 9, second = 42)
```

```
Out [9] datetime.time(9, 0, 42)
```

The `time` constructor uses a 24-hour clock; we can pass it an `hour` value greater than or equal to 12 to represent a time in the afternoon or evening,. The next example models 19:43:22 or, equivalently, 7:43:22 p.m.:

```
In [10] dt.time(hour = 19, minute = 43, second = 22)
```

```
Out [10] datetime.time(19, 43, 22)
```

The `time` object saves our constructor arguments as object attributes. We can access their values with the `hour`, `minute`, and `second` attributes:

```
In [11] alarm_clock.hour  
Out [11] 6  
  
In [12] alarm_clock.minute  
Out [12] 43  
  
In [13] alarm_clock.second  
Out [13] 25
```

Next in line is the `datetime` object, which holds both a date and a time. Its first six parameters are the `year`, `month`, `day`, `hour`, `minute`, and `second`:

```
In [14] # The two lines below are equivalent  
moon_landing = dt.datetime(1969, 7, 20, 22, 56, 20)  
moon_landing = dt.datetime(  
    year = 1969,  
    month = 7,  
    day = 20,  
    hour = 22,  
    minute = 56,  
    second = 20  
)  
moon_landing  
  
Out [14] datetime.datetime(1969, 7, 20, 22, 56, 20)
```

The `year`, `month`, and `day` parameters are required. The time-related attributes are optional and default to 0. The next example models midnight on January 1, 2020 (12:00:00 a.m.). We explicitly pass in the `year`, `month`, and `day` parameters; the `hour`, `minute`, and `second` parameters implicitly fall back to 0:

```
In [15] dt.datetime(2020, 1, 1)  
Out [15] datetime.datetime(2020, 1, 1, 0, 0)
```

Our final noteworthy object from the `datetime` module is `timedelta`, which models a duration—a length of time. Its constructor’s parameters include `weeks`, `days`, and `hours`. All the parameters are optional and default to 0. The constructor adds the time lengths to calculate the total duration. In the next example, we add 8 weeks and 6 days for a total of 62 days (8 weeks * 7 days + 6 days). Python also adds 3 hours, 58 minutes, and 12 seconds for a grand total of 14,292 seconds (238 minutes * 60 seconds + 12 seconds):

```
In [16] dt.timedelta(  
    weeks = 8,  
    days = 6,  
    hours = 3,
```

```

        minutes = 58,
        seconds = 12
    )

Out [16] datetime.timedelta(days=62, seconds=14292)

```

Now that we've familiarized ourselves with how Python models dates, times, and durations, let's explore how pandas builds on these concepts.

11.1.2 How pandas works with datetimes

Python's `datetime` module has had its share of criticism. Some common complaints include

- A large number of modules to keep track of. We introduced only `datetime` in this chapter, but additional modules are available for calendars, time conversions, utility functions, and more.
- A large number of classes to remember.
- Complex, difficult object APIs for time-zone logic.

Pandas introduces the `Timestamp` object as a replacement for Python's `datetime` object. We can view the `Timestamp` and `datetime` objects as being siblings; they are often interchangeable in the pandas ecosystem, such as when being passed as method arguments. Much as the `Series` expands on a Python list, the `Timestamp` adds features to the more primitive `datetime` object. We'll see some of these bells and whistles as we progress through the chapter.

The `Timestamp` constructor is available at the top level of pandas; it accepts the same parameters as a `datetime` constructor. The three date-related parameters (`year`, `month`, and `day`) are required. Time-related parameters are optional and default to 0. Here, we again model April 12, 1991, a glorious day:

```

In [17] # The two lines below are equivalent
       pd.Timestamp(1991, 4, 12)
       pd.Timestamp(year = 1991, month = 4, day = 12)

Out [17] Timestamp('1991-04-12 00:00:00')

```

Pandas considers a `Timestamp` to be equal to a `date/datetime` if the two objects store the same information. We can use the `==` symbols to compare object equality:

```

In [18] (pd.Timestamp(year = 1991, month = 4, day = 12)
       == dt.date(year = 1991, month = 4, day = 12))

Out [18] True

In [19] (pd.Timestamp(year = 1991, month = 4, day = 12, minute = 2)
       == dt.datetime(year = 1991, month = 4, day = 12, minute = 2))

Out [19] True

```

The two objects will be unequal if there is any difference in date or time. The next example instantiates a `Timestamp` with a minute value of 2 and a `datetime` with a minute value of 1. The equality comparison yields `False`:

```
In [20] (pd.Timestamp(year = 1991, month = 4, day = 12, minute = 2)
       == dt.datetime(year = 1991, month = 4, day = 12, minute = 1))

Out [20] False
```

The `Timestamp` constructor is remarkably flexible and accepts a variety of inputs. The next example passes the constructor a string instead of a sequence of integers. The text stores a date in the common YYYY-MM-DD format (four-digit year, two-digit month, two-digit day). Pandas correctly deciphers the month, day, and year from the input:

```
In [21] pd.Timestamp("2015-03-31")

Out [21] Timestamp('2015-03-31 00:00:00')
```

Pandas recognizes many standard datetime string formats. The next example replaces the dashes in the date string with slashes:

```
In [22] pd.Timestamp("2015/03/31")

Out [22] Timestamp('2015-03-31 00:00:00')
```

The next example passes a string in MM/DD/YYYY format, which is no problem for pandas:

```
In [23] pd.Timestamp("03/31/2015")

Out [23] Timestamp('2015-03-31 00:00:00')
```

We can also include the time in a variety of written formats:

```
In [24] pd.Timestamp("2021-03-08 08:35:15")

Out [24] Timestamp('2021-03-08 08:35:15')

In [25] pd.Timestamp("2021-03-08 6:13:29 PM")

Out [25] Timestamp('2021-03-08 18:13:29')
```

Finally, the `Timestamp` constructor accepts Python's native `date`, `time`, and `datetime` objects. The next example parses data from a `datetime` object:

```
In [26] pd.Timestamp(dt.datetime(2000, 2, 3, 21, 35, 22))

Out [26] Timestamp('2000-02-03 21:35:22')
```

The `Timestamp` object implements all `datetime` attributes, such as `hour`, `minute`, and `second`. The next example saves the previous `Timestamp` to a variable and then outputs several attributes:

```
In [27] my_time = pd.Timestamp(dt.datetime(2000, 2, 3, 21, 35, 22))
        print(my_time.year)
        print(my_time.month)
        print(my_time.day)
        print(my_time.hour)
        print(my_time.minute)
        print(my_time.second)
```

```
Out [27]: 2000  
          2  
          3  
          21  
          35  
          22
```

Pandas does its best to ensure that its datetime objects work similarly to Python's built-in ones. We can consider the objects to be effectively swappable in pandas operations.

11.2 Storing multiple timestamps in a DatetimeIndex

An `index` is the collection of identifier labels attached to a pandas data structure. The most common index we've encountered so far is the `RangeIndex`, a sequence of ascending or descending numeric values. We can access the index of a `Series` or a `DataFrame` via the `index` attribute:

```
In [28] pd.Series([1, 2, 3]).index  
Out [28] RangeIndex(start=0, stop=3, step=1)
```

Pandas uses an `Index` object to store a collection of string labels. In the next example, notice that the index object pandas attaches to a `Series` changes based on its contents:

```
In [29] pd.Series([1, 2, 3], index = ["A", "B", "C"]).index  
Out[29] Index(['A', 'B', 'C'], dtype='object')
```

The `DatetimeIndex` is an index for storing `Timestamp` objects. If we pass a list of `Timestamps` to the `Series` constructor's `index` parameter, pandas will attach a `DatetimeIndex` to the `Series`:

```
In [30]: timestamps = [
    pd.Timestamp("2020-01-01"),
    pd.Timestamp("2020-02-01"),
    pd.Timestamp("2020-03-01"),
]
pd.Series([1, 2, 3], index = timestamps).index

Out[30]: DatetimeIndex(['2020-01-01', '2020-02-01', '2020-03-01'],
   dtype='datetime64[ns]', freq=None)
```

Pandas will also use a `DatetimeIndex` if we pass a list of Python `datetime` objects:

```
In [31]: datetimes = [
    dt.datetime(2020, 1, 1),
    dt.datetime(2020, 2, 1),
    dt.datetime(2020, 3, 1),
]
pd.Series([1, 2, 3], index = datetimes).index

Out[31]: DatetimeIndex(['2020-01-01', '2020-02-01', '2020-03-01'],
   dtype='datetime64[ns]', freq=None)
```

We can also create a `DatetimeIndex` from scratch. Its constructor is available at the top level of pandas. The constructor's `data` parameter accepts any iterable collection of dates. We can pass the dates as strings, datetimes, `Timestamps`, or even a mix of data types. Pandas will convert all values to equivalent `Timestamps` and store them within the index:

```
In [32] string_dates = ["2018/01/02", "2016/04/12", "2009/09/07"]
       pd.DatetimeIndex(data = string_dates)

Out [32] DatetimeIndex(['2018-01-02', '2016-04-12', '2009-09-07'],
                       dtype='datetime64[ns]', freq=None)

In [33] mixed_dates = [
           dt.date(2018, 1, 2),
           "2016/04/12",
           pd.Timestamp(2009, 9, 7)
       ]

       dt_index = pd.DatetimeIndex(mixed_dates)
       dt_index

Out [33] DatetimeIndex(['2018-01-02', '2016-04-12', '2009-09-07'],
                       dtype='datetime64[ns]', freq=None)
```

Now that we have a `DatetimeIndex` assigned to a `dt_index` variable, let's attach it to a pandas data structure. The next example connects the index to a sample `Series`:

```
In [34] s = pd.Series(data = [100, 200, 300], index = dt_index)
       s

Out [34] 2018-01-02    100
          2016-04-12    200
          2009-09-07    300
          dtype: int64
```

Date- and time-related operations become possible in pandas only when we store our values as `Timestamps` rather than strings. Pandas can't deduce a day of the week from a string like "2018-01-02" because it views it as being a collection of digits and dashes, not an actual date. That's why it's imperative to convert all relevant string columns to datetimes when importing a data set for the first time.

We can use the `sort_index` method to sort a `DatetimeIndex` in ascending or descending order. The next example sorts the index dates in ascending order (earliest to latest):

```
In [35] s.sort_index()

Out [35] 2009-09-07    300
          2016-04-12    200
          2018-01-02    100
          dtype: int64
```

Pandas accounts for both date and time when sorting or comparing datetimes. If two `Timestamps` use the same date, pandas will compare their hours, minutes, seconds, and so on.

A variety of sorting and comparison operations are available for Timestamps out of the box. The less-than symbol (`<`) , for example, checks whether one Timestamp occurs earlier than another:

```
In [36] morning = pd.Timestamp("2020-01-01 11:23:22 AM")
        evening = pd.Timestamp("2020-01-01 11:23:22 PM")

        morning < evening

Out [36] True
```

In section 11.7, we'll learn how to apply these types of comparisons to all values in a Series.

11.3 Converting column or index values to datetimes

Our first data set for this chapter, `disney.csv`, holds nearly 60 years' worth of stock prices for the Walt Disney Company, one of the world's most recognized entertainment brands. Each row includes a date, the stock's highest and lowest value throughout that day, and its opening and closing price:

```
In [37] disney = pd.read_csv("disney.csv")
        disney.head()

Out [37]
```

| | Date | High | Low | Open | Close |
|---|------------|----------|----------|----------|----------|
| 0 | 1962-01-02 | 0.096026 | 0.092908 | 0.092908 | 0.092908 |
| 1 | 1962-01-03 | 0.094467 | 0.092908 | 0.092908 | 0.094155 |
| 2 | 1962-01-04 | 0.094467 | 0.093532 | 0.094155 | 0.094155 |
| 3 | 1962-01-05 | 0.094779 | 0.093844 | 0.094155 | 0.094467 |
| 4 | 1962-01-08 | 0.095714 | 0.092285 | 0.094467 | 0.094155 |

The `read_csv` function defaults to importing all values in non-numeric columns as strings. We can access the `dtypes` attribute on the `DataFrame` to see the columns' data types. Notice that the Date column has a data type of "object", the pandas designation for a string:

```
In [38] disney.dtypes

Out [38] Date      object
          High     float64
          Low      float64
          Open     float64
          Close    float64
          dtype: object
```

We must explicitly tell pandas which columns' values to convert to datetimes. One option we've seen before is the `read_csv` function's `parse_dates` parameter, introduced in chapter 3. We can pass the parameter a list of columns whose values pandas should convert to datetimes:

```
In [39] disney = pd.read_csv("disney.csv", parse_dates = ["Date"])
```

An alternative solution is the `to_datetime` conversion function at the top level of pandas. The function accepts an iterable object (such as a Python list, tuple, `Series`, or `index`), converts its values to datetimes, and returns the new values in a `DatetimeIndex`. Here's a small example:

```
In [40] string_dates = ["2015-01-01", "2016-02-02", "2017-03-03"]
       dt_index = pd.to_datetime(string_dates)
       dt_index

Out [40] DatetimeIndex(['2015-01-01', '2016-02-02', '2017-03-03'],
                       dtype='datetime64[ns]', freq=None)
```

Let's pass the Date Series from the `disney` DataFrame to the `to_datetime` function:

```
In [41] pd.to_datetime(disney["Date"]).head()

Out [41] 0    1962-01-02
         1    1962-01-03
         2    1962-01-04
         3    1962-01-05
         4    1962-01-08
Name: Date, dtype: datetime64[ns]
```

We've got a `Series` of datetimes, so let's overwrite the original DataFrame. The next code sample replaces the original Date column with the new datetime `Series`. Remember that Python evaluates the right side of an equal sign first:

```
In [42] disney["Date"] = pd.to_datetime(disney["Date"])
```

Let's check on the Date column again via the `dtypes` attribute:

```
In [43] disney.dtypes

Out [43] Date      datetime64[ns]
          High     float64
          Low      float64
          Open     float64
          Close    float64
          dtype: object
```

Excellent; we have a datetime column! With our Date values stored correctly, we can explore the powerful datetime functionalities that pandas provides out of the box.

11.4 Using the `DatetimeProperties` object

A datetime `Series` holds a special `dt` attribute that exposes a `DatetimeProperties` object:

```
In [44] disney["Date"].dt

Out [44] <pandas.core.indexes.accessors.DatetimeProperties object at
          0x116247950>
```

We can access attributes and invoke methods on the `DatetimeProperties` object to extract information from the columns' datetime values. The `dt` attribute is to datetimes what the `str` attribute is to strings. (See chapter 6 for a review of `str`.) Both attributes specialize in manipulations of a specific type of data.

Let's begin our exploration of the `DatetimeProperties` object with the `day` attribute, which pulls out the day from each date. Pandas returns the values in a new `Series`:

```
In [45] disney["Date"].head(3)

Out [45] 0    1962-01-02
          1    1962-01-03
          2    1962-01-04
          Name: Date, dtype: datetime64[ns]

In [46] disney["Date"].dt.day.head(3)

Out [46] 0    2
          1    3
          2    4
          Name: Date, dtype: int64
```

The `month` attribute returns a `Series` with the month numbers. January has a `month` value of 1, February has a `month` value of 2, and so on. It's important to note that this is different from how we typically count in Python/pandas, where we assign the first item a value of 0:

```
In [47] disney["Date"].dt.month.head(3)

Out [47] 0    1
          1    1
          2    1
          Name: Date, dtype: int64
```

The `year` attribute returns a new `Series` with the years:

```
In [48] disney["Date"].dt.year.head(3)

Out [48] 0    1962
          1    1962
          2    1962
          Name: Date, dtype: int64
```

The previous attributes are pretty simple. We can ask pandas to extract more-interesting pieces of information. One example is the `dayofweek` attribute, which returns a `Series` of numbers for each date's day of the week. 0 denotes Monday, 1 denotes Tuesday, and so on up to 6 for Sunday. In the following output, the value of 1 at index position 0 indicates that January 2, 1962, fell on a Tuesday:

```
In [49] disney["Date"].dt.dayofweek.head()

Out [49] 0    1
          1    2
          2    3
          3    4
```

```
4      0
Name: Date, dtype: int64
```

What if we wanted the weekday's name instead of its number? The `day_name` method does the trick. Be careful with the syntax. We invoke the method on the `dt` object, not on the `Series` itself:

```
In [50] disney["Date"].dt.day_name().head()
```

```
Out [50] 0      Tuesday
         1      Wednesday
         2     Thursday
         3     Friday
         4    Monday
Name: Date, dtype: object
```

We can pair these `dt` attributes and methods with other pandas features for advanced analyses. Here's an example. Let's calculate the average performance of Disney's stock by weekday. We'll begin by attaching the `Series` returned from the `dt.day_name` method to the `disney DataFrame`:

```
In [51] disney["Day of Week"] = disney["Date"].dt.day_name()
```

We can group the rows based on the values in the new Day of Week column (a technique introduced in chapter 7):

```
In [52] group = disney.groupby("Day of Week")
```

We can invoke the `GroupBy` object's `mean` method to calculate the average of values for each grouping:

```
In [53] group.mean()
```

```
Out [53]
```

| | High | Low | Open | Close |
|--------------------|-------------|------------|-------------|--------------|
| Day of Week | | | | |
| Friday | 23.767304 | 23.318898 | 23.552872 | 23.554498 |
| Monday | 23.377271 | 22.930606 | 23.161392 | 23.162543 |
| Thursday | 23.770234 | 23.288687 | 23.534561 | 23.540359 |
| Tuesday | 23.791234 | 23.335267 | 23.571755 | 23.562907 |
| Wednesday | 23.842743 | 23.355419 | 23.605618 | 23.609873 |

In three lines of code, we've calculated the average stock performance by day of week.

Let's come back to `dt` object methods. The complementary `month_name` method returns a `Series` with the dates' month names:

```
In [54] disney["Date"].dt.month_name().head()
```

```
Out [54] 0      January
         1      January
         2      January
         3      January
         4      January
Name: Date, dtype: object
```

Some attributes on the `dt` object return Booleans. Suppose that we want to explore Disney's stock performance at the start of each quarter in its history. The four quarters of a business year start on January 1, April 1, July 1, and October 1. The `is_quarter_start` attribute returns a Boolean Series in which `True` denotes that the row's date fell on a quarter start day:

```
In [55] disney["Date"].dt.is_quarter_start.tail()

Out [55] 14722    False
          14723    False
          14724    False
          14725    True
          14726    False
Name: Date, dtype: bool
```

We can use the Boolean Series to extract the `disney` rows that fell at the beginning of a quarter. The next example uses the familiar square-bracket syntax to pull out the rows:

```
In [56] disney[disney["Date"].dt.is_quarter_start].head()

Out [56]
```

| Date | High | Low | Open | Close | Day of Week |
|----------------|----------|----------|----------|----------|-------------|
| 189 1962-10-01 | 0.064849 | 0.062355 | 0.063913 | 0.062355 | Monday |
| 314 1963-04-01 | 0.087989 | 0.086704 | 0.087025 | 0.086704 | Monday |
| 377 1963-07-01 | 0.096338 | 0.095053 | 0.096338 | 0.095696 | Monday |
| 441 1963-10-01 | 0.110467 | 0.107898 | 0.107898 | 0.110467 | Tuesday |
| 565 1964-04-01 | 0.116248 | 0.112394 | 0.112394 | 0.116248 | Wednesday |

We can use the `is_quarter_end` attribute to pull out dates that fell at the end of a quarter:

```
In [57] disney[disney["Date"].dt.is_quarter_end].head()

Out [57]
```

| Date | High | Low | Open | Close | Day of Week |
|----------------|----------|----------|----------|----------|-------------|
| 251 1962-12-31 | 0.074501 | 0.071290 | 0.074501 | 0.072253 | Monday |
| 440 1963-09-30 | 0.109825 | 0.105972 | 0.108541 | 0.107577 | Monday |
| 502 1963-12-31 | 0.101476 | 0.096980 | 0.097622 | 0.101476 | Tuesday |
| 564 1964-03-31 | 0.115605 | 0.112394 | 0.114963 | 0.112394 | Tuesday |
| 628 1964-06-30 | 0.101476 | 0.100191 | 0.101476 | 0.100834 | Tuesday |

The complementary `is_month_start` and `is_month_end` attributes confirm that a date fell at the beginning or end of a month:

```
In [58] disney[disney["Date"].dt.is_month_start].head()

Out [58]
```

| Date | High | Low | Open | Close | Day of Week |
|----------------|----------|----------|----------|----------|-------------|
| 22 1962-02-01 | 0.096338 | 0.093532 | 0.093532 | 0.094779 | Thursday |
| 41 1962-03-01 | 0.095714 | 0.093532 | 0.093532 | 0.095714 | Thursday |
| 83 1962-05-01 | 0.087296 | 0.085426 | 0.085738 | 0.086673 | Tuesday |
| 105 1962-06-01 | 0.079814 | 0.077943 | 0.079814 | 0.079814 | Friday |
| 147 1962-08-01 | 0.068590 | 0.068278 | 0.068590 | 0.068590 | Wednesday |

```
In [59] disney[disney["Date"].dt.is_month_end].head()
Out [59]
```

| | Date | High | Low | Open | Close | Day of Week |
|-----|------------|----------|----------|----------|----------|-------------|
| 21 | 1962-01-31 | 0.093844 | 0.092908 | 0.093532 | 0.093532 | Wednesday |
| 40 | 1962-02-28 | 0.094779 | 0.093220 | 0.094155 | 0.093220 | Wednesday |
| 82 | 1962-04-30 | 0.087608 | 0.085738 | 0.087608 | 0.085738 | Monday |
| 104 | 1962-05-31 | 0.082308 | 0.079814 | 0.079814 | 0.079814 | Thursday |
| 146 | 1962-07-31 | 0.069214 | 0.068278 | 0.068278 | 0.068590 | Tuesday |

The `is_year_start` attribute returns True if a date falls at the start of a year. The next example returns an empty DataFrame; the stock market is closed on New Year's Day, so no dates in the data set fit the criteria:

```
In [60] disney[disney["Date"].dt.is_year_start].head()
Out [60]
```

| Date | High | Low | Open | Close | Day of Week |
|------|------|-----|------|-------|-------------|
| | | | | | |

The complementary `is_year_end` attribute returns True if a date falls at the end of a year:

```
In [61] disney[disney["Date"].dt.is_year_end].head()
Out [61]
```

| Date | High | Low | Open | Close | Day of Week | |
|------|------------|----------|----------|----------|-------------|----------|
| 251 | 1962-12-31 | 0.074501 | 0.071290 | 0.074501 | 0.072253 | Monday |
| 502 | 1963-12-31 | 0.101476 | 0.096980 | 0.097622 | 0.101476 | Tuesday |
| 755 | 1964-12-31 | 0.117853 | 0.116890 | 0.116890 | 0.116890 | Thursday |
| 1007 | 1965-12-31 | 0.154141 | 0.150929 | 0.153498 | 0.152214 | Friday |
| 1736 | 1968-12-31 | 0.439301 | 0.431594 | 0.434163 | 0.436732 | Tuesday |

Regardless of the attribute, the filtering process remains the same: create a Boolean Series and then pass it inside square brackets after the DataFrame.

11.5 Adding and subtracting durations of time

We can add or subtract consistent durations of time with the `DateOffset` object. Its constructor is available at the top level of pandas. The constructor accepts parameters for years, months, days, and more. The next example models a time of three years, four months, and three days:

```
In [62] pd.DateOffset(years = 3, months = 4, days = 5)
Out [62] <DateOffset: days=5, months=4, years=3>
```

Here's a reminder of the first five rows of the `disney` DataFrame:

```
In [63] disney["Date"].head()
Out [63] 0    1962-01-02
          1    1962-01-03
          2    1962-01-04
```

```
3    1962-01-05
4    1962-01-08
Name: Date, dtype: datetime64[ns]
```

For the sake of example, let's imagine that our recordkeeping system malfunctioned, and the dates in the Date column are off by five days. We can add a consistent amount of time to each date in a datetime Series with a plus sign (+) and a DateOffset object. The plus sign means "move forward" or "into the future." The next example adds five days to each date in the Date column:

```
In [64] (disney["Date"] + pd.DateOffset(days = 5)).head()

Out [64] 0    1962-01-07
          1    1962-01-08
          2    1962-01-09
          3    1962-01-10
          4    1962-01-13
Name: Date, dtype: datetime64[ns]
```

When paired with a DateOffset, the minus sign (-) subtracts a duration from each date in a datetime Series. The minus sign means "move backward" or "into the past." The next example moves each date back three days:

```
In [65] (disney["Date"] - pd.DateOffset(days = 3)).head()

Out [65] 0    1961-12-30
          1    1961-12-31
          2    1962-01-01
          3    1962-01-02
          4    1962-01-05
Name: Date, dtype: datetime64[ns]
```

Although the previous output does not show it, the Timestamp objects *do* store a time internally. When we converted the Date column's values to datetimes, pandas assumed a time of midnight for each date. The next example adds an hours parameter to the DateOffset constructor to add a consistent time to each datetime in Date. The resulting Series displays the date and time:

```
In [66] (disney["Date"] + pd.DateOffset(days = 10, hours = 6)).head()

Out [66] 0    1962-01-12 06:00:00
          1    1962-01-13 06:00:00
          2    1962-01-14 06:00:00
          3    1962-01-15 06:00:00
          4    1962-01-18 06:00:00
Name: Date, dtype: datetime64[ns]
```

Pandas applies the same logic when subtracting a duration. The next example subtracts one year, three months, ten days, six hours, and three minutes from each date:

```
In [67] (
        disney["Date"]
        - pd.DateOffset(
            years = 1, months = 3, days = 10, hours = 6, minutes = 3
```

```
)  
).head()  
  
Out [67]: 0    1960-09-21 17:57:00  
         1    1960-09-22 17:57:00  
         2    1960-09-23 17:57:00  
         3    1960-09-24 17:57:00  
         4    1960-09-27 17:57:00  
Name: Date, dtype: datetime64[ns]
```

The `DateOffset` constructor supports additional keyword parameters for seconds, microseconds, and nanoseconds. See the pandas documentation for more info.

11.6 Date offsets

The `DateOffset` object is optimal for adding or subtracting a consistent amount of time to or from each date. Real-world analyses often demand a more dynamic calculation. Let's say we want to round each date to the end of its current month. Each date is a different number of days from the end of its month, so a consistent `DateOffset` addition won't suffice.

Pandas ships with prebuilt offset objects for dynamic time-based calculations. These objects are defined in `offsets.py`, a module within the library. In our code, we have to prefix these offsets with their complete path: `pd.offsets`.

One sample offset is `MonthEnd`, which rounds each date to the next month-end. Here's a refresher on the last five rows in the Date column:

```
In [68]: disney["Date"].tail()  
  
Out [68]: 14722    2020-06-26  
          14723    2020-06-29  
          14724    2020-06-30  
          14725    2020-07-01  
          14726    2020-07-02  
Name: Date, dtype: datetime64[ns]
```

We can apply the addition and subtraction syntax from section 11.5 to pandas' offset objects. The next example returns a new `Series` that rounds each datetime to the month-end. The plus sign moves forward in time, so we move to the next month-end:

```
In [69]: (disney["Date"] + pd.offsets.MonthEnd()).tail()  
  
Out [69]: 14722    2020-06-30  
          14723    2020-06-30  
          14724    2020-07-31  
          14725    2020-07-31  
          14726    2020-07-31  
Name: Date, dtype: datetime64[ns]
```

There has to be some movement in the intended direction. Pandas cannot round a date to the same date. Thus, if a date falls at the end of a month, the library rounds it to the end of the following month. Pandas rounds 2020-06-30 at index position 14724 to 2020-07-31, the next available month-end.

The minus sign moves each date backward in time. The next example uses the MonthEnd offset to round the dates to the previous month-end. Pandas rounds the first three dates (2020-06-26, 2020-06-29, and 2020-06-30) to 2020-05-31, the last day in May. It rounds the final two dates (2020-07-01 and 2020-07-02) to 2020-06-30, the last day in June:

```
In [70] (disney["Date"] - pd.offsets.MonthEnd()).tail()

Out [70] 14722    2020-05-31
         14723    2020-05-31
         14724    2020-05-31
         14725    2020-06-30
         14726    2020-06-30
Name: Date, dtype: datetime64[ns]
```

The complementary MonthBegin offset rounds to the first date of a month. The next example uses a + sign to round each date to the next month's beginning. Pandas rounds the first three dates (2020-06-26, 2020-06-29, and 2020-06-30) to 2020-07-01, the beginning of July. Pandas rounds the two remaining July dates (2020-07-01 and 2020-07-02) to 2020-08-01, the first day of August:

```
In [71] (disney["Date"] + pd.offsets.MonthBegin()).tail()

Out [71] 14722    2020-07-01
         14723    2020-07-01
         14724    2020-07-01
         14725    2020-08-01
         14726    2020-08-01
Name: Date, dtype: datetime64[ns]
```

We can pair the MonthBegin offset with the minus sign to round dates backward to the beginning of a month. In the next example, pandas rounds the first three dates (2020-06-26, 2020-06-29, and 2020-06-30) to the start of June, 2020-06-01. It rounds the last date, 2020-07-02, to the beginning of July, 2020-07-01. The curious case is 2020-07-01 at index position 14725. As we mentioned earlier, pandas cannot round a date to the same date. There has to be some movement backward, so pandas rounds to the previous month's start, 2020-06-01:

```
In [72] (disney["Date"] - pd.offsets.MonthBegin()).tail()

Out [72] 14722    2020-06-01
         14723    2020-06-01
         14724    2020-06-01
         14725    2020-06-01
         14726    2020-07-01
Name: Date, dtype: datetime64[ns]
```

A special group of offsets is available for business time calculations; their names begin with a capital "B". The Business Month End (BMonthEnd) offset, for example, rounds to the month's last business day. The five business days are Monday, Tuesday, Wednesday, Thursday, and Friday.

Consider the following Series of three datetimes. The three dates fall on Thursday, Friday, and Saturday, respectively:

```
In [73] may_dates = ["2020-05-28", "2020-05-29", "2020-05-30"]
      end_of_may = pd.Series(pd.to_datetime(may_dates))
      end_of_may

Out [73] 0    2020-05-28
         1    2020-05-29
         2    2020-05-30
      dtype: datetime64[ns]
```

Let's compare the MonthEnd and BMonthEnd offsets. When we pair the MonthEnd offset with a plus sign, pandas rounds all three dates to the last day of May, 2020-05-31. Whether that date falls on a business day or the weekend is irrelevant:

```
In [74] end_of_may + pd.offsets.MonthEnd()

Out [74] 0    2020-05-31
         1    2020-05-31
         2    2020-05-31
      dtype: datetime64[ns]
```

The BMonthEnd offset returns a different set of results. The last business day of May 2020 is Friday, May 29. Pandas rounds the first date in the Series, 2020-05-28, to the 29th. The next date, 2020-05-29, falls *on* the month's last business date. Pandas cannot round a date to the same date, so it rounds 2020-05-29 to June's last business day, 2020-06-30, a Tuesday. The last date in the Series, 2020-05-30, is a Saturday. No business days are left in May, so pandas similarly rounds the date to June's last business day, 2020-06-30:

```
In [75] end_of_may + pd.offsets.BMonthEnd()

Out [75] 0    2020-05-29
         1    2020-06-30
         2    2020-06-30
      dtype: datetime64[ns]
```

The pd.offsets module includes additional offsets for rounding to the starts and ends of quarters, business quarters, years, business years, and more. Feel free to explore them in your free time.

11.7 The Timedelta object

You may recall Python's native timedelta object from earlier in the chapter. A timedelta models duration—the distance between two times. A duration such as one hour represents a length of time; it does not have a specific date or time attached. Pandas models a duration with its own Timedelta object.

NOTE It's easy to confuse the two objects. timedelta is built into Python, whereas Timedelta is built into pandas. The two are interchangeable when used with pandas operations.

The `Timedelta` constructor is available at the top level of pandas. It accepts keyword parameters for units of time such as days, hours, minutes, and seconds. The next example instantiates a `Timedelta` modeling eight days, seven hours, six minutes, and five seconds:

```
In [76] duration = pd.Timedelta(
    days = 8,
    hours = 7,
    minutes = 6,
    seconds = 5
)
duration

Out [76] Timedelta('8 days 07:06:05')
```

The `to_timedelta` function at the top level of pandas converts its argument to a `Timedelta` object. We can pass in a string, as in the next example:

```
In [77] duration = pd.to_timedelta("3 hours, 5 minutes, 12 seconds")
Out [77] Timedelta('0 days 03:05:12')
```

We can also pass an integer to the `to_timedelta` function along with a unit parameter. The unit parameter declares the unit of time that the number represents. Accepted arguments include "hour", "day", and "minute". The next example's `Timedelta` models a five-hour duration:

```
In [78] pd.to_timedelta(5, unit = "hour")
Out [78] Timedelta('0 days 05:00:00')
```

We can pass an iterable object such as a list to the `to_timedelta` function to convert its values to `Timedeltas`. Pandas will store the `Timedeltas` in a `TimedeltaIndex`, a pandas index for storing durations:

```
In [79] pd.to_timedelta([5, 10, 15], unit = "day")
Out [79] TimedeltaIndex(['5 days', '10 days', '15 days'],
                       dtype='timedelta64[ns]', freq=None)
```

Usually, `Timedelta` objects are derived rather than created from scratch. The subtraction of one `Timestamp` from another, for example, returns a `Timedelta` automatically:

```
In [80] pd.Timestamp("1999-02-05") - pd.Timestamp("1998-05-24")
Out [80] Timedelta('257 days 00:00:00')
```

Now that we've gotten acquainted with `Timedeltas`, let's import our second data set for the chapter: `deliveries.csv`. The CSV tracks product shipments for a fictional company. Each row includes an order date and a delivery date:

```
In [81] deliveries = pd.read_csv("deliveries.csv")
       deliveries.head()

Out [81]



|   | order_date | delivery_date |
|---|------------|---------------|
| 0 | 5/24/98    | 2/5/99        |
| 1 | 4/22/92    | 3/6/98        |
| 2 | 2/10/91    | 8/26/92       |
| 3 | 7/21/92    | 11/20/97      |
| 4 | 9/2/93     | 6/10/98       |


```

Let's practice converting the values in the two columns to datetimes. Yes, we can use the `parse_dates` parameter, but let's try another approach. One option is invoking the `to_datetime` function twice, once for the `order_date` column and once for the `delivery_date` column, and overwriting the existing DataFrame columns:

```
In [82] deliveries["order_date"] = pd.to_datetime(
           deliveries["order_date"])
        )

deliveries["delivery_date"] = pd.to_datetime(
           deliveries["delivery_date"])
        )
```

A more scalable solution is to iterate over the column names with a `for` loop. We can reference a `deliveries` column dynamically, use `to_datetime` to create a DatetimeIndex of Timestamps from it, and then overwrite the original column:

```
In [83] for column in ["order_date", "delivery_date"]:
           deliveries[column] = pd.to_datetime(deliveries[column])
```

Let's take a look at `deliveries`. The new column format confirms that we've converted the strings to datetimes:

```
In [84] deliveries.head()
```

```
Out [84]
```

| | order_date | delivery_date |
|---|------------|---------------|
| 0 | 1998-05-24 | 1999-02-05 |
| 1 | 1992-04-22 | 1998-03-06 |
| 2 | 1991-02-10 | 1992-08-26 |
| 3 | 1992-07-21 | 1997-11-20 |
| 4 | 1993-09-02 | 1998-06-10 |

Let's calculate the duration of each shipment. With pandas, this calculation is as simple as subtracting the `order_date` column from the `delivery_date` column:

```
In [85] (deliveries["delivery_date"] - deliveries["order_date"]).head()

Out [85] 0    257 days
         1   2144 days
         2    563 days
```

```
3    1948 days
4    1742 days
dtype: timedelta64[ns]
```

Pandas returns a Series of timedeltas. Let's attach the new Series to the end of the deliveries DataFrame:

```
In [86] deliveries["duration"] = (
    deliveries["delivery_date"] - deliveries["order_date"]
)
deliveries.head()

Out [86]
```

| | order_date | delivery_date | duration |
|---|-------------------|----------------------|-----------------|
| 0 | 1998-05-24 | 1999-02-05 | 257 days |
| 1 | 1992-04-22 | 1998-03-06 | 2144 days |
| 2 | 1991-02-10 | 1992-08-26 | 563 days |
| 3 | 1992-07-21 | 1997-11-20 | 1948 days |
| 4 | 1993-09-02 | 1998-06-10 | 1742 days |

Now we have two Timestamp columns and one Timedelta column:

```
In [87] deliveries.dtypes

Out [87] order_date        datetime64[ns]
         delivery_date      datetime64[ns]
         duration          timedelta64[ns]
         dtype: object
```

We can add or subtract Timedeltas from Timestamp objects. The next example subtracts each row's duration from the delivery_date column. Predictably, the values in the new Series are identical to the values in the order_date column:

```
In [88] (deliveries["delivery_date"] - deliveries["duration"]).head()

Out [88] 0    1998-05-24
         1    1992-04-22
         2    1991-02-10
         3    1992-07-21
         4    1993-09-02
         dtype: datetime64[ns]
```

A plus symbol adds a Timedelta to a Timestamp. Let's say we wanted to find the date of delivery if each package took twice as long to arrive. We can add the Timedelta values in the duration column to the Timestamp values in the delivery_date column:

```
In [89] (deliveries["delivery_date"] + deliveries["duration"]).head()

Out [89] 0    1999-10-20
         1    2004-01-18
         2    1994-03-12
         3    2003-03-22
         4    2003-03-18
         dtype: datetime64[ns]
```

The `sort_values` method works with Timedelta Series. The next example sorts the duration column in ascending order, from the shortest delivery to the longest one:

```
In [90] deliveries.sort_values("duration")

Out [90]
      order_date  delivery_date   duration
454  1990-05-24    1990-06-01    8 days
294  1994-08-11    1994-08-20    9 days
10   1998-05-10    1998-05-19    9 days
499  1993-06-03    1993-06-13   10 days
143  1997-09-20    1997-10-06   16 days
...
152  1990-09-18    1999-12-19  3379 days
62   1990-04-02    1999-08-16  3423 days
458  1990-02-13    1999-11-15  3562 days
145  1990-03-07    1999-12-25  3580 days
448  1990-01-20    1999-11-12  3583 days

501 rows × 3 columns
```

Mathematical methods are also available on Timedelta Series. The next few examples highlight three methods we've used throughout the book: `max` for the largest value, `min` for the smallest value, and `mean` for the average:

```
In [91] deliveries["duration"].max()

Out [91] Timedelta('3583 days 00:00:00')

In [92] deliveries["duration"].min()

Out [92] Timedelta('8 days 00:00:00')

In [93] deliveries["duration"].mean()

Out [93] Timedelta('1217 days 22:53:53.532934')
```

Here's the next challenge. Let's filter the DataFrame for packages that took more than a year to deliver. We can use the greater-than symbol (`>`) to compare each duration column value to a fixed duration. We can specify the length of time as a Timedelta or as a string. The next example uses "365 days":

```
In [94] # The two lines below are equivalent
        (deliveries["duration"] > pd.Timedelta(days = 365)).head()
        (deliveries["duration"] > "365 days").head()

Out [94] 0      False
         1      True
         2      True
         3      True
         4      True
Name: Delivery Time, dtype: bool
```

Let's use the Boolean Series to filter for the deliveries rows with a delivery time greater than 365 days:

```
In [95] deliveries[deliveries["duration"] > "365 days"].head()
```

```
Out [95]
```

| | order_date | delivery_date | duration |
|---|------------|---------------|-----------|
| 1 | 1992-04-22 | 1998-03-06 | 2144 days |
| 2 | 1991-02-10 | 1992-08-26 | 563 days |
| 3 | 1992-07-21 | 1997-11-20 | 1948 days |
| 4 | 1993-09-02 | 1998-06-10 | 1742 days |
| 6 | 1990-01-25 | 1994-10-02 | 1711 days |

We can get as granular as needed with the comparison duration. The next example includes the days, hours, and minutes in the string, separating the units of time with commas:

```
In [96] long_time = (
    deliveries["duration"] > "2000 days, 8 hours, 4 minutes"
)
deliveries[long_time].head()
```

```
Out [96]
```

| | order_date | delivery_date | duration |
|----|------------|---------------|-----------|
| 1 | 1992-04-22 | 1998-03-06 | 2144 days |
| 7 | 1992-02-23 | 1998-12-30 | 2502 days |
| 11 | 1992-10-17 | 1998-10-06 | 2180 days |
| 12 | 1992-05-30 | 1999-08-15 | 2633 days |
| 15 | 1990-01-20 | 1998-07-24 | 3107 days |

As a reminder, Pandas can sort Timedelta columns. To discover the longest or shortest durations, we can invoke the `sort_values` method on the duration Series.

11.8 Coding challenge

Here's your chance to practice the concepts introduced in this chapter.

11.8.1 Problems

Citi Bike NYC is New York City's official bike-sharing program. Residents and tourists can pick up and drop off bicycles at hundreds of locations around the city. Ride data is publicly available and released monthly by the city at <https://www.citibikenyc.com/system-data>. `citibike.csv` is a collection of ~1.9 million rides that cyclists took in June 2020. For simplicity's sake, the data set has been modified from its original version and includes only two columns: each ride's start time and end time. Let's import the data set and assign it to a `citi_bike` variable:

```
In [97] citi_bike = pd.read_csv("citibike.csv")
citi_bike.head()
```

```
Out [97]
```

| | start_time | stop_time |
|---|--------------------------|--------------------------|
| 0 | 2020-06-01 00:00:03.3720 | 2020-06-01 00:17:46.2080 |
| 1 | 2020-06-01 00:00:03.5530 | 2020-06-01 01:03:33.9360 |
| 2 | 2020-06-01 00:00:09.6140 | 2020-06-01 00:17:06.8330 |
| 3 | 2020-06-01 00:00:12.1780 | 2020-06-01 00:03:58.8640 |
| 4 | 2020-06-01 00:00:21.2550 | 2020-06-01 00:24:18.9650 |

The datetime entries in the start_time and stop_time columns include the year, month, day, hour, minute, second, and microsecond. (A *microsecond* is a unit of time equal to one millionth of a second.)

We can use the info method to print a summary that includes the DataFrame's length, the columns' data types, and the memory use. Notice that pandas has imported the two columns' values as strings:

```
In [98]: citi_bike.info()

Out [98]

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1882273 entries, 0 to 1882272
Data columns (total 2 columns):
 #   Column      Dtype  
--- 
 0   start_time  object 
 1   stop_time   object 
dtypes: object(2)
memory usage: 28.7+ MB
```

Here are the challenges for this section:

- 1 Convert the start_time and stop_time columns to store datetime (Timestamp) values instead of strings.
- 2 Count the rides that occurred on each day of the week (Monday, Tuesday, and so on). Which weekday is the most popular for a bike ride? Use the start_time column as your starting point.
- 3 Count the rides per week for each week within the month. To do so, round each date in the start_time column to its previous or current Monday. Assume that each week starts on a Monday and ends on a Sunday. Thus, the first week of June would be Monday, June 1 through Sunday, June 7.
- 4 Calculate the duration of each ride, and save the results to a new duration column.
- 5 Find the average duration of a bike ride.
- 6 Extract the five longest bike rides by duration from the data set.

11.8.2 Solutions

Let's tackle the problems one by one:

- 1 The to_datetime conversion function at the top level of pandas works well to convert the start_time and end_time columns' values to Timestamps. The next

code sample iterates over a list of the column names with a `for` loop, passes each column into the `to_datetime` function, and overwrites the existing string column with the new datetime `Series`:

```
In [99] for column in ["start_time", "stop_time"]:
    citi_bike[column] = pd.to_datetime(citi_bike[column])
```

Let's invoke the `info` method again to confirm that the two columns store date-time values:

```
In [100] citi_bike.info()

Out [100]

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1882273 entries, 0 to 1882272
Data columns (total 2 columns):
 #   Column      Dtype  
 ---  --  
 0   start_time  datetime64[ns]
 1   stop_time   datetime64[ns]
 dtypes: datetime64[ns](2)
memory usage: 28.7 MB
```

- 2 We'll have to take two steps to count the number of bike rides per weekday. First, we extract the weekday from each datetime in the `start_time` column; then we count the weekdays' occurrences. The `dt.day_name` method returns a `Series` with the weekday names for each date:

```
In [101] citi_bike["start_time"].dt.day_name().head()

Out [101] 0    Monday
          1    Monday
          2    Monday
          3    Monday
          4    Monday
Name: start_time, dtype: object
```

Then we can invoke the trusty `value_counts` method on the returned `Series` to count the weekdays. In June 2020, Tuesday was the most popular day for a bike ride:

```
In [102] citi_bike["start_time"].dt.day_name().value_counts()

Out [102] Tuesday      305833
          Sunday       301482
          Monday       292690
          Saturday     285966
          Friday        258479
          Wednesday    222647
          Thursday     215176
Name: start_time, dtype: int64
```

- 3 The next challenge requires us to group each date into its corresponding week bucket. We can do so by rounding the date to its previous or current Monday. Here's a clever solution: we can use the `dayofweek` attribute to return a Series of numbers. 0 denotes Monday, 1 denotes Tuesday, 6 denotes Sunday, and so on:

```
In [103] citi_bike["start_time"].dt.dayofweek.head()

Out [103] 0      0
           1      0
           2      0
           3      0
           4      0
Name: start_time, dtype: int64
```

The weekday number also represents the distance in days from the closest Monday. Monday, June 1, for example, has a `dayofweek` value of 0. The date is 0 days away from the closest Monday. Similarly, Tuesday, June 2, has a `dayofweek` value of 1. The date is one day away from the closest Monday (June 1). Let's save this Series to a `days_away_from_monday` variable:

```
In [104] days_away_from_monday = citi_bike["start_time"].dt.dayofweek
```

If we subtract a date's `dayofweek` value from the date itself, we'll effectively round each date to its previous Monday. We can pass the `dayofweek` Series into the `to_timedelta` function to convert it to a Series of durations. We'll pass a unit parameter set to "day" to tell pandas to treat the numeric values as the number of days:

```
In [105] citi_bike["start_time"] - pd.to_timedelta(
            days_away_from_monday, unit = "day"
        )

Out [105] 0      2020-06-01 00:00:03.372
           1      2020-06-01 00:00:03.553
           2      2020-06-01 00:00:09.614
           3      2020-06-01 00:00:12.178
           4      2020-06-01 00:00:21.255
...
1882268  2020-06-29 23:59:41.116
1882269  2020-06-29 23:59:46.426
1882270  2020-06-29 23:59:47.477
1882271  2020-06-29 23:59:53.395
1882272  2020-06-29 23:59:53.901
Name: start_time, Length: 1882273, dtype: datetime64[ns]
```

Let's save the new Series to a `dates_rounded_to_monday` variable:

```
In [106] dates_rounded_to_monday = citi_bike[
            "start_time"
        ] - pd.to_timedelta(days_away_from_monday, unit = "day")
```

We're halfway there. We've rounded the dates to the correct Mondays, but the `value_counts` method won't work yet. The differences in times between the dates will lead pandas to deem them unequal:

```
In [107] dates_rounded_to_monday.value_counts().head()

Out [107] 2020-06-22 20:13:36.208      3
           2020-06-08 17:17:26.335      3
           2020-06-08 16:50:44.596      3
           2020-06-15 19:24:26.737      3
           2020-06-08 19:49:21.686      3
Name: start_time, dtype: int64
```

Let's use the `dt.date` attribute to return a `Series` with the dates from each datetime:

```
In [108] dates_rounded_to_monday.dt.date.head()

Out [108] 0    2020-06-01
           1    2020-06-01
           2    2020-06-01
           3    2020-06-01
           4    2020-06-01
Name: start_time, dtype: object
```

Now that we've isolated the dates, we can invoke the `value_counts` method to count each value's occurrences. The week of Monday, June 15 to Sunday, June 21 saw the highest number of bike rides throughout the month:

```
In [109] dates_rounded_to_monday.dt.date.value_counts()

Out [109] 2020-06-15    481211
           2020-06-08    471384
           2020-06-22    465412
           2020-06-01    337590
           2020-06-29    126676
Name: start_time, dtype: int64
```

- 4 To calculate each ride's duration, we can subtract the `start_time` column from the `stop_time` column. Pandas will return a `Series` of `Timedeltas`. We'll need to save this `Series` for the next example, so let's attach it to the `DataFrame` as a new column called `duration`:

```
In [110] citi_bike["duration"] = (
    citi_bike["stop_time"] - citi_bike["start_time"]
)
citi_bike.head()
```

Out [110]

| | start_time | stop_time | duration |
|---|-------------------------|-------------------------|------------------------|
| 0 | 2020-06-01 00:00:03.372 | 2020-06-01 00:17:46.208 | 0 days 00:17:42.836000 |
| 1 | 2020-06-01 00:00:03.553 | 2020-06-01 01:03:33.936 | 0 days 01:03:30.383000 |
| 2 | 2020-06-01 00:00:09.614 | 2020-06-01 00:17:06.833 | 0 days 00:16:57.219000 |

```
3 2020-06-01 00:00:12.178 2020-06-01 00:03:58.864 0 days 00:03:46.686000
4 2020-06-01 00:00:21.255 2020-06-01 00:24:18.965 0 days 00:23:57.710000
```

Note that the previous subtraction would raise an error if the columns were storing strings; that's why it's imperative to convert them to datetimes first.

- 5 Next up, we have to find the average duration of all bike rides. This process is a simple one: we can invoke the mean method on the new duration column for the calculation. The average ride was 27 minutes and 19 seconds:

```
In [111] citi_bike["duration"].mean()
Out [111] Timedelta('0 days 00:27:19.590506853')
```

- 6 The final question asks to identify the five longest bike rides in the data set. One solution is to sort the duration column values in descending order with the sort_values method and then use the head method to view the first five rows. These sessions likely belonged to people who forgot to check their bikes in after finishing their ride:

```
In [112] citi_bike["duration"].sort_values(ascending = False).head()
Out [112] 50593    32 days 15:01:54.940000
98339     31 days 01:47:20.632000
52306     30 days 19:32:20.696000
15171     30 days 04:26:48.424000
149761    28 days 09:24:50.696000
Name: duration, dtype: timedelta64[ns]
```

Another option is the nlargest method. We can invoke this method on either the duration Series or the DataFrame as a whole. Let's go with the latter approach:

```
In [113] citi_bike.nlargest(n = 5, columns = "duration")
Out [113]
      start_time      stop_time      duration
50593 2020-06-01 21:30:17... 2020-07-04 12:32:12... 32 days 15:01:54.94...
98339 2020-06-02 19:41:39... 2020-07-03 21:29:00... 31 days 01:47:20.63...
52306 2020-06-01 22:17:10... 2020-07-02 17:49:31... 30 days 19:32:20.69...
15171 2020-06-01 13:01:41... 2020-07-01 17:28:30... 30 days 04:26:48.42...
149761 2020-06-04 14:36:53... 2020-07-03 00:01:44... 28 days 09:24:50.69...
```

There you have it: the five longest bike rides in the data set. Congratulations on completing the coding challenge!

Summary

- The pandas Timestamp object is a flexible, powerful replacement for Python's native datetime object.
- The dt accessor on a datetime Series reveals a DatetimeProperties object with attributes and methods for extracting the day, month, weekday name, and more.

- The `Timedelta` object models a duration.
- Pandas creates a `Timedelta` object when we subtract two `Timestamp` objects from each other.
- The offsets in the `pd.offsets` package dynamically round dates to the closest week, month, quarter, and more. We can round forward with the plus sign and backward with the minus sign.
- A `DatetimeIndex` is a container for `Timestamp` values. We can add it as an index or column to a pandas data structure.
- The `TimedeltaIndex` is a container for `Timedelta` objects.
- The top-level `to_datetime` function converts an iterable of values to a `DatetimeIndex` of `Timestamps`.

12

Imports and exports

This chapter covers

- Importing JSON data
- Flattening a nested collection of records
- Downloading a CSV from an online website
- Reading from and writing to Excel workbooks

Data sets come in a variety of file formats: comma-separated values (CSV), tab-separated values (TSV), Excel workbooks (XLSX), and more. Some data formats do not store data in tabular format; instead, they nest collections of related data inside a key-value store. Consider the following two examples. Figure 12.1 stores data in a table, and figure 12.2 stores the same data in a Python dictionary.

| Year | Award | Winner |
|------|--------------|-------------------|
| 2000 | Best Actor | Russell Crowe |
| 2000 | Best Actress | Julia Roberts |
| 2001 | Best Actor | Denzel Washington |
| 2001 | Best Actress | Halle Berry |

Figure 12.1 A table of Oscar winners

Python's dictionary is an example of a key-value data structure:

```
{
  2000: [
    {
      "Award": "Best Actor",
      "Winner": "Russell Crowe"
    },
    {
      "Award": "Best Actress",
      "Winner": "Julia Roberts"
    }
  ],
  2001: [
    {
      "Award": "Best Actor",
      "Winner": "Denzel Washington"
    },
    {
      "Award": "Best Actress",
      "Winner": "Halle Berry"
    }
  ]
}
```

Figure 12.2 A Python dictionary (key-value store) with the same data

Pandas ships with utility functions to manipulate key-value data into tabular data and vice versa. When we have the data in a `DataFrame`, we can apply all our favorite techniques to it. But contorting the data into the right shape often proves to be the most challenging part of an analysis. In this chapter, we'll learn how to resolve common problems in data imports. We'll also explore the other side of the equation: exporting `DataFrames` to various file types and data structures.

12.1 Reading from and writing to JSON files

Let's kick things off by talking about JSON, perhaps the most popular key-value storage format available today. *JavaScript Object Notation* (JSON) is a format for storing and transferring text data. Although the JavaScript programming language inspires its syntax, JSON itself is language-independent. Most languages today, including Python, can generate and parse JSON.

A JSON response consists of key-value pairs, in which a key serves as a unique identifier for a value. The colon symbol (`:`) connects a key to a value:

```
"name": "Harry Potter"
```

Keys must be strings. Values can be of any data type, including strings, numbers, and Booleans. JSON is similar to Python's dictionary object.

JSON is a popular response format for many modern application programming interfaces (APIs), such as website servers. A raw JSON response from an API looks like a plain string. Here's what a response might look like:

```
{"name": "Harry Potter", "age": 17, "wizard": true}
```

Software programs called *linters* format JSON responses by placing each key-value pair on a separate line. One popular example is JSONLint (<https://jsonlint.com>). Running the previous JSON through JSONLint produces the following output:

```
{
    "name": "Harry Potter",
    "age": 17,
    "wizard": true,
}
```

There is no technical difference between the two preceding code samples, but the latter is more readable.

The JSON response holds three key-value pairs:

- The "name" key has a string value of "Harry Potter".
- The "age" key has an integer value of 17.
- The "wizard" key has a Boolean value of true. In JSON, Booleans are spelled in lowercase. The concept is identical to a Python Boolean.

A key can also point to an *array*, an ordered collection of elements equivalent to a Python list. The "friends" key in the next JSON example maps to an array of two strings:

```
{
    "name": "Harry Potter",
    "age": 17,
    "wizard": true,
    "friends": ["Ron Weasley", "Hermione Granger"],
}
```

JSON can store additional key-value pairs within nested objects, such as "address" in the following example. In Pythonic terms, we can think of "address" as a dictionary nested within another dictionary:

```
{
    "name": "Harry Potter",
    "age": 17,
    "wizard": true,
    "friends": ["Ron Weasley", "Hermione Granger"],
    "address": {
        "street": "4 Privet Drive",
        "town": "Little Whinging"
    }
}
```

Nested stores of key-value pairs help simplify the data by grouping related fields.

12.1.1 Loading a JSON file Into a DataFrame

Let's create a new Jupyter Notebook and import the pandas library. Make sure to create the Notebook in the same directory as this chapter's data files:

```
In [1] import pandas as pd
```

JSON can be stored in a plain-text file with a .json extension. This chapter's prizes.json file is a saved JSON response from the Nobel Prize API. The API stores Nobel Prize laureates dating back to 1901. You can view the raw JSON response in your web browser by navigating to <http://api.nobelprize.org/v1/prize.json>. Here's a preview of the JSON shape:

```
{
  "prizes": [
    {
      "year": "2019",
      "category": "chemistry",
      "laureates": [
        {
          "id": "976",
          "firstname": "John",
          "surname": "Goodenough",
          "motivation": "\"for the development of lithium-ion batteries\"",
          "share": "3"
        },
        {
          "id": "977",
          "firstname": "M. Stanley",
          "surname": "Whittingham",
          "motivation": "\"for the development of lithium-ion batteries\"",
          "share": "3"
        },
        {
          "id": "978",
          "firstname": "Akira",
          "surname": "Yoshino",
          "motivation": "\"for the development of lithium-ion batteries\"",
          "share": "3"
        }
      ]
    },
  ]
```

The JSON consists of a top-level `prizes` key that maps to an array of dictionaries, one for each combination of year and category ("chemistry", "physics", "literature", and so on). The `"year"` and `"category"` keys are present for all winners, whereas the `"laureates"` and `"overallMotivation"` keys are present for only some. Here's a sample dictionary with an `"overallMotivation"` key:

```
{
  year: "1972",
  category: "peace",
  overallMotivation: "No Nobel Prize was awarded this year. The prize money for 1972 was allocated to the Main Fund."
}
```

The "laureates" key connects to an array of dictionaries, each with its own "id", "firstname", "surname", "motivation", and "share" keys. The "laureates" key stores an array to accommodate years in which multiple people were awarded a Nobel Prize in the same category. The "laureates" key uses a list even if a year had only one winner. Here is an example:

```
{
    year: "2019",
    category: "literature",
    laureates: [
        {
            id: "980",
            firstname: "Peter",
            surname: "Handke",
            motivation: "for an influential work that with linguistic
                        ingenuity has explored the periphery and the specificity of
                        human experience",
            share: "1"
        }
    ]
},
```

Import functions in pandas have a consistent naming scheme; each one consists of a read prefix followed by a file type. We've used the `read_csv` function many times throughout the book, for example. To import a JSON file, we'll use the complementary `read_json` function. Its first argument is the file path. The next example passes the `nobel.json` file. Pandas returns a one-column DataFrame with a `prizes` column:

```
In [2] nobel = pd.read_json("nobel.json")
nobel.head()

Out [2]
```

| | prizes |
|---|--|
| 0 | {'year': '2019', 'category': 'chemistry', 'laureates': [{...}], ...} |
| 1 | {'year': '2019', 'category': 'economics', 'laureates': [{...}], ...} |
| 2 | {'year': '2019', 'category': 'literature', 'laureates': [{...}], ...} |
| 3 | {'year': '2019', 'category': 'peace', 'laureates': [{...}], ...} |
| 4 | {'year': '2019', 'category': 'physics', 'overallMotivation': '"for...}'} |

We've successfully imported the file into pandas, but unfortunately, not in a format that's ideal for analysis. Pandas set the JSON's top-level `prizes` key as the column name and created a Python dictionary for each key-value pair it parsed from the JSON. Here's a sample row value:

```
In [3] nobel.loc[2, "prizes"]

Out [3] {'year': '2019',
         'category': 'literature',
         'laureates': [{...}],
         'firstname': 'Peter',
         'surname': 'Handke', ...}
```

```
'motivation': '"for an influential work that with linguistic
    ingenuity has explored the periphery and the specificity of
    human experience"',
'share': '1'}]}}
```

The next example passes the row value into Python’s built-in `type` function. We indeed have a Series of dictionaries:

```
In [4] type(nobel.loc[2, "prizes"])
Out [4] dict
```

Our goal is to convert the data to tabular format. To do so, we’ll need to extract the JSON’s top-level key-value pairs (`year`, `category`) to separate DataFrame columns. We’ll also need to iterate over each dictionary in the “`laureates`” list and extract its nested information. Our goal is a separate row for each Nobel laureate, connected to their year and category. The DataFrame we’re aiming for looks like this:

| | id | firstname | surname | motivation | share | year | category |
|---|-----------|------------------|----------------|--|--------------|-------------|-----------------|
| 0 | 976 | John | Goodenough | "for the development of lithium-ion batteries" | 3 | 2019 | chemistry |
| 1 | 977 | M. Stanley | Whittingham | "for the development of lithium-ion batteries" | 3 | 2019 | chemistry |
| 2 | 978 | Akira | Yoshino | "for the development of lithium-ion batteries" | 3 | 2019 | chemistry |

The process of moving nested records of data into a single, one-dimensional list is called *flattening* or *normalizing*. The pandas library includes a built-in `json_normalize` function to take care of the heavy lifting. Let’s try it on a small example: a sample dictionary from the `nobel` DataFrame. We’ll use the `loc` accessor to access the first row’s dictionary and assign it to a `chemistry_2019` variable:

```
In [5] chemistry_2019 = nobel.loc[0, "prizes"]
chemistry_2019

Out [5] {'year': '2019',
         'category': 'chemistry',
         'laureates': [{'id': '976',
                        'firstname': 'John',
                        'surname': 'Goodenough',
                        'motivation': '"for the development of lithium-ion batteries"',
                        'share': '3'},
                       {'id': '977',
                        'firstname': 'M. Stanley',
                        'surname': 'Whittingham',
                        'motivation': '"for the development of lithium-ion batteries"',
                        'share': '3'},
                       {'id': '978',
                        'firstname': 'Akira',
                        'surname': 'Yoshino',
                        'motivation': '"for the development of lithium-ion batteries"',
                        'share': '3'}]}
```

Let’s pass the `chemistry_2019` dictionary to the `json_normalize` function’s `data` parameter. The good news is that pandas extracts the three top-level dictionary keys (“`year`”, “`category`”, and “`laureates`”) to separate columns in a new

DataFrame. Unfortunately, the library still keeps the nested dictionaries from the "laureates" list. Ultimately, we'd like to store the data in separate columns.

```
In [6] pd.json_normalize(data = chemistry_2019)
Out [6]
      year   category
0  2019  chemistry  [{"id": "976", "firstname": "John", "surname": ...}
```

We can use the `json_normalize` function's `record_path` parameter to normalize the nested "laureates" records. We pass the parameter a string denoting which key in the dictionary holds the nested records. Let's pass it "laureates":

```
In [7] pd.json_normalize(data = chemistry_2019, record_path = "laureates")
Out [7]
      id   firstname     surname      motivation share
0  976       John  Goodenough  "for the development of li...      3
1  977  M. Stanley  Whittingham  "for the development of li...      3
2  978       Akira    Yoshino  "for the development of li...      3
```

One step forward, one step back. Pandas expanded the nested "laureates" dictionaries into new columns, but now we've lost the original year and category columns. To preserve these top-level key-value pairs, we can pass a list with their names to a parameter called `meta`:

```
In [8] pd.json_normalize(
        data = chemistry_2019,
        record_path = "laureates",
        meta = ["year", "category"],
    )
Out [8]
      id   firstname     surname      motivation share   year   category
0  976       John  Goodenough  "for the develop...      3  2019  chemistry
1  977  M. Stanley  Whittingham  "for the develop...      3  2019  chemistry
2  978       Akira    Yoshino  "for the develop...      3  2019  chemistry
```

That's exactly the DataFrame we want. Our normalization strategy has worked successfully on a single dictionary from the prizes column. Luckily, the `json_normalize` function is smart enough to accept a Series of dictionaries and repeat the extraction logic for each entry. Let's see what happens when we pass it the `prizes` Series:

```
In [9] pd.json_normalize(
        data = nobel["prizes"],
        record_path = "laureates",
        meta = ["year", "category"]
    )
-----
KeyError                                     Traceback (most recent call last)
<ipython-input-49-e09a24c19e5b> in <module>
      2     data = nobel["prizes"],
```

```

3      record_path = "laureates",
----> 4      meta = ["year", "category"]
5 )

KeyError: 'laureates'

```

Unfortunately, Pandas raises a `KeyError` exception. Some dictionaries in the `prizes` Series do not have a "`laureates`" key. The `json_normalize` function is unable to extract nested laureates information from a nonexistent list. One way we can solve this problem is to identify the dictionaries that lack a "`laureates`" key and manually assign them the key. In those situations, we can provide the "`laureates`" key a value of an empty list.

Let's take a second to review the `setdefault` method on a Python dictionary. Consider this dictionary:

```

In [10] cheese_consumption = {
        "France": 57.9,
        "Germany": 53.2,
        "Luxembourg": 53.2
    }

```

The `setdefault` method assigns a key-value pair to a dictionary, but only if the dictionary does not have the key. If the key exists, the method returns its existing value. The method's first argument is the key, and its second argument is the value.

The following example attempts to add the key "`France`" to the `cheese_consumption` dictionary with a value of 100. The key exists, so nothing changes. Python keeps the original value of 57.9:

```

In [11] cheese_consumption.setdefault("France", 100)
Out [11] 57.9

In [12] cheese_consumption["France"]

Out [12] 57.9

```

By comparison, the next example invokes `setdefault` with an argument of "`Italy`". The key "`Italy`" does not exist in the dictionary, so Python adds it and assigns it a value of 48:

```

In [13] cheese_consumption.setdefault("Italy", 48)
Out [13] 48

In [14] cheese_consumption

Out [14] {'France': 57.9, 'Germany': 53.2, 'Luxembourg': 53.2, 'Italy': 48}

```

Let's apply this technique to each nested dictionary within `prizes`. If a dictionary does not have a `laureates` key, we'll use the `setdefault` method to add the key with a value of an empty list. As a reminder, we can use the `apply` method to iterate individually over each `Series` element. This method, introduced in chapter 3, accepts a

function as an argument and passes each Series row to the function in sequence. The next example defines an `add_laureates_key` function to update a single dictionary and then passes the function to the `apply` method as an argument:

```
In [15] def add_laureates_key(entry):
         entry.setdefault("laureates", [])
         nobel["prizes"].apply(add_laureates_key)

Out [15] 0      [{"id": "976", "firstname": "John", "surname": ...}
  1      [{"id": "982", "firstname": "Abhijit", "surname": ...}
  2      [{"id": "980", "firstname": "Peter", "surname": ...}
  3      [{"id": "981", "firstname": "Abiy", "surname": ...}
  4      [{"id": "973", "firstname": "James", "surname": ...}
 ...
  641     [{"id": "160", "firstname": "Jacobus H.", "surname": ...}
  642     [{"id": "569", "firstname": "Sully", "surname": ...}
  643     [{"id": "462", "firstname": "Henry", "surname": ...}
  644     [{"id": "1", "firstname": "Wilhelm Conrad", "surname": ...}
  645     [{"id": "293", "firstname": "Emil", "surname": ...}
Name: prizes, Length: 646, dtype: object
```

The `setdefault` method mutates the dictionaries within `prizes`, so there is no need to overwrite the original Series.

Now that all nested dictionaries have a `laureates` key, we can reinvoke the `json_normalize` function. Once again, we'll pass a list to the `meta` parameter with the two top-level dictionary keys we'd like to keep. We'll also use `record_path` to specify the top-level attribute with a nested list of records:

```
In [16] winners = pd.json_normalize(
            data = nobel["prizes"],
            record_path = "laureates",
            meta = ["year", "category"]
        )

winners

Out [16]
```

| | id | firstname | surname | motivation | share | year | category |
|-----|-----------|------------------|----------------|-------------------|--------------|-------------|-----------------|
| 0 | 976 | John | Goodenough | "for the de... | 3 | 2019 | chemistry |
| 1 | 977 | M. Stanley | Whittingham | "for the de... | 3 | 2019 | chemistry |
| 2 | 978 | Akira | Yoshino | "for the de... | 3 | 2019 | chemistry |
| 3 | 982 | Abhijit | Banerjee | "for their ... | 3 | 2019 | economics |
| 4 | 983 | Esther | Duflo | "for their ... | 3 | 2019 | economics |
| ... | ... | ... | ... | ... | ... | ... | ... |
| 945 | 569 | Sully | Prudhomme | "in special... | 1 | 1901 | literature |
| 946 | 462 | Henry | Dunant | "for his hu... | 2 | 1901 | peace |
| 947 | 463 | Frédéric | Passy | "for his li... | 2 | 1901 | peace |
| 948 | 1 | Wilhelm Con... | Röntgen | "in recogni... | 1 | 1901 | physics |
| 949 | 293 | Emil von | Behring | "for his wo... | 1 | 1901 | medicine |

950 rows × 7 columns

Success! We've normalized the JSON data, converted it to tabular format, and stored it in a two-dimensional DataFrame.

12.1.2 Exporting a DataFrame to a JSON file

Now let's attempt the process in reverse: converting a DataFrame to a JSON representation and writing it to a JSON file. The `to_json` method creates a JSON string from a pandas data structure; its `orient` parameter customizes the format in which pandas returns the data. The next example uses an argument of "records" to return a JSON array of key-value objects. Pandas stores the column names as dictionary keys that point to the row's respective values. Here's an example with the first two rows of winners, the DataFrame we created in section 12.1.1:

```
In [17] winners.head(2)

Out [17]


|   | <b>id</b> | <b>firstname</b> | <b>surname</b> | <b>motivation</b>                              | <b>share</b> | <b>year</b> | <b>category</b> |
|---|-----------|------------------|----------------|------------------------------------------------|--------------|-------------|-----------------|
| 0 | 976       | John             | Goodenough     | "for the development of lithium-ion batteries" | 3            | 2019        | chemistry       |
| 1 | 977       | M. Stanley       | Whittingham    | "for the development of lithium-ion batteries" | 3            | 2019        | chemistry       |



In [18] winners.head(2).to_json(orient = "records")

Out [18]
'[{"id": "976", "firstname": "John", "surname": "Goodenough", "motivation": "\\"for the development of lithium-ion batteries\\\"", "share": "3", "year": "2019", "category": "chemistry"}, {"id": "977", "firstname": "M. Stanley", "surname": "Whittingham", "motivation": "\\"for the development of lithium-ion batteries\\\"", "share": "3", "year": "2019", "category": "chemistry"}]'
```

By comparison, we can pass an argument of "split" to return a dictionary with separate columns, index, and data keys. This option prevents the duplication of column names for each row entry:

```
In [19] winners.head(2).to_json(orient = "split")

Out [19]
{'columns': ["id", "firstname", "surname", "motivation", "share", "year", "category"], "index": [0, 1], "data": [{"id": "976", "firstname": "John", "surname": "Goodenough", "motivation": "\\"for the development of lithium-ion batteries\\\"", "share": "3", "year": "2019", "category": "chemistry"}, {"id": "977", "firstname": "M. Stanley", "surname": "Whittingham", "motivation": "\\"for the development of lithium-ion batteries\\\"", "share": "3", "year": "2019", "category": "chemistry"}]}
```

Additional arguments available for the `orient` parameter include "index", "columns", "values", and "table".

When the JSON format fits your expectations, pass the JSON file name as the first argument to the `to_json` method. Pandas will write the string to a JSON file in the same directory as the Jupyter Notebook:

```
In [20] winners.to_json("winners.json", orient = "records")
```

WARNING Be mindful when executing the same cell twice. If a `winners.json` file exists in the directory, pandas will overwrite it when we execute the previous cell. The library will not warn us that it is replacing the file. For this reason, I strongly recommend giving output files a different name from input files.

12.2 Reading from and writing to CSV files

Our next data set is a collection of baby names in New York City. Each row includes the name, birth year, gender, ethnicity, count, and popularity rank. The CSV file is hosted on New York City's government website and is available at <http://mng.bz/MgzQ>.

We can access the website in our web browser and download the CSV file to our computer for local storage. As an alternative, we can pass the URL as the first argument to the `read_csv` function. Pandas will automatically fetch the data set and import it into a `DataFrame`. Hardcoded URLs are helpful when we have real-time data that changes frequently because they save us the manual work of downloading the data set each time we rerun our analysis:

```
In [21] url = "https://data.cityofnewyork.us/api/views/25th-nujf/rows.csv"
       baby_names = pd.read_csv(url)
       baby_names.head()
```

```
Out [21]
```

| | Year of Birth | Gender | Ethnicity | Child's First Name | Count | Rank |
|---|---------------|--------|-----------|--------------------|-------|------|
| 0 | 2011 | FEMALE | HISPANIC | GERALDINE | 13 | 75 |
| 1 | 2011 | FEMALE | HISPANIC | GIA | 21 | 67 |
| 2 | 2011 | FEMALE | HISPANIC | GIANNA | 49 | 42 |
| 3 | 2011 | FEMALE | HISPANIC | GISELLE | 38 | 51 |
| 4 | 2011 | FEMALE | HISPANIC | GRACE | 36 | 53 |

Note that pandas will raise an `HTTPError` exception if the link is invalid.

Let's try writing the `baby_names` `DataFrame` to a plain CSV file with the `to_csv` method. Without an argument, the method outputs the CSV string directly in our Jupyter Notebook. Following CSV conventions, pandas separates rows with line breaks and row values with commas. As a reminder, a `\n` character marks a line break in Python. Here's a small preview of the method's output for the first ten rows of `baby_names`:

```
In [22] baby_names.head(10).to_csv()
```

```
Out [22]
```

```
",Year of Birth,Gender,Ethnicity,Child's First
Name,Count,Rank\n0,2011,FEMALE,HISPANIC,GERALDINE,13,75\n1,2011,FEMALE,HISPANIC,GIA,21,67\n2,2011,FEMALE,HISPANIC,GIANNA,49,42\n3,2011,FEMALE,HISPANIC,GISELLE,38,51\n4,2011,FEMALE,HISPANIC,GRACE,36,53\n5,2011,FEMALE,HISPANIC,GUADALUPE,26,62\n6,2011,FEMALE,HISPANIC,HAILEY,126,8\n7,2011,FEMALE,HISPANIC,HAILEY,14,74\n8,2011,FEMALE,HISPANIC,HANNAH,17,71\n9,2011,FEMALE,HISPANIC,HAYLEE,17,71\n"
```

By default, pandas includes the `DataFrame` index in the CSV string. Notice the comma at the beginning of the string and the numeric values (0, 1, 2, and so on) after each \n symbol. Figure 12.3 highlights the commas in the output from the `to_csv` method.

```
",Year of Birth,Gender,Ethnicity,Child's First
Name,Count,Rank\n0,2011,FEMALE,HISPANIC,GERALDINE,13,75\n1,2011,FEMALE,HISPANIC,GIA,21,67\n2,2011,FEMALE,HISPANIC,GIANNA,49,42\n3,2011,FEMALE,HISPANIC,GISELLE,38,51\n4,2011,FEMALE,HISPANIC,GRACE,36,53\n5,2011,FEMALE,HISPANIC,GUADALUPE,26,62\n6,2011,FEMALE,HISPANIC,HAILEY,126,8\n7,2011,FEMALE,HISPANIC,HALEY,14,74\n8,2011,FEMALE,HISPANIC,HANNAH,17,71\n9,2011,FEMALE,HISPANIC,HAYLEE,17,71\n"
```

Figure 12.3 The CSV output with arrows highlighting the index labels

We can exclude the index by passing the `index` parameter an argument of `False`:

```
In [23] baby_names.head(10).to_csv(index = False)

Out [23]

"Year of Birth,Gender,Ethnicity,Child's First
Name,Count,Rank\n2011,FEMALE,HISPANIC,GERALDINE,13,75\n2011,FEMALE,HISPANIC,GIA,21,67\n2011,FEMALE,HISPANIC,GIANNA,49,42\n2011,FEMALE,HISPANIC,GISELLE,38,51\n2011,FEMALE,HISPANIC,GRACE,36,53\n2011,FEMALE,HISPANIC,GUADALUPE,26,62\n2011,FEMALE,HISPANIC,HAILEY,126,8\n2011,FEMALE,HISPANIC,HALEY,14,74\n2011,FEMALE,HISPANIC,HANNAH,17,71\n2011,FEMALE,HISPANIC,HAYLEE,17,71\n"
```

To write the string to a CSV file, we can pass the desired filename as the first argument to the `to_csv` method. Make sure to include the `.csv` extension in the string. If we do not provide a specific path, pandas will write the file to the same directory as the Jupyter Notebook:

```
In [24] baby_names.to_csv("NYC_Baby_Names.csv", index = False)
```

The method produces no output below the Notebook cell. If we flip back to the Jupyter Notebook navigation interface, however, we see that pandas has created the CSV file. Figure 12.4 shows the saved `NYC_Baby_Names.csv` file.



Figure 12.4 The `NYC_Baby_Names.csv` file saved to the same directory as the Jupyter Notebook

By default, pandas writes all `DataFrame` columns to the CSV file. We can choose which columns to export by passing a list of names to the `columns` parameter. The next example creates a CSV with only the Gender, Child's First Name, and Count columns:

```
In [25]: baby_names.to_csv(  
    "NYC_Baby_Names.csv",  
    index = False,  
    columns = ["Gender", "Child's First Name", "Count"]  
)
```

Please note that if a `NYC_Baby_Names.csv` file exists in the directory, pandas will overwrite the existing file.

12.3 Reading from and writing to Excel workbooks

Excel is the most popular spreadsheet application in use today. Pandas makes it easy to read from and write to Excel workbooks and even specific worksheets. But first, we'll need to do a little housekeeping to integrate the two pieces of software.

12.3.1 Installing the `xlrd` and `openpyxl` libraries in an Anaconda environment

Pandas needs the `xlrd` and `openpyxl` libraries to interact with Excel. These packages are the glue that connects Python to Excel.

Here's a refresher on installing a package in an Anaconda environment. For a more in-depth overview, see appendix A. If you've already installed these libraries in your Anaconda environment, feel free to skip to section 12.3.2.

- 1 Launch the Terminal (macOS) or Anaconda Prompt (Windows) application.
- 2 Use the `conda info --envs` command to see your available Anaconda environments:

```
$ conda info --envs  
  
# conda environments:  
#  
base                  * /opt/anaconda3  
pandas_in_action      /opt/anaconda3/envs/pandas_in_action
```

- 3 Activate the Anaconda environment in which you'd like to install the libraries. Appendix A shows how to create a `pandas_in_action` environment for this book. If you chose a different environment name, replace `pandas_in_action` with it in the following command:

```
$ conda activate pandas_in_action
```

- 4 Install the `xlrd` and `openpyxl` libraries with the `conda install` command:

(pandas_in_action) \$ conda install xlrd openpyxl
- 5 When Anaconda lists the required package dependencies, enter "Y" and press Enter to start the installation.

- 6 When the installation completes, execute `jupyter notebook` to start the Jupyter server again, and navigate back to the Jupyter Notebook for the chapter.

Don't forget to execute the cell with the `import pandas as pd` command at the top.

12.3.2 Importing Excel workbooks

The `read_excel` function at the top level of pandas imports an Excel workbook into a `DataFrame`. Its first parameter, `io`, accepts a string with the workbook's path. Make sure to include the `.xlsx` extension in the filename. By default, pandas will import only the first worksheet in the workbook.

The `Single Worksheet.xlsx` Excel workbook is a good place to start because it contains a single Data worksheet:

```
In [26] pd.read_excel("Single Worksheet.xlsx")
```

```
Out [26]
```

| | First Name | Last Name | City | Gender |
|---|------------|-----------|---------------|--------|
| 0 | Brandon | James | Miami | M |
| 1 | Sean | Hawkins | Denver | M |
| 2 | Judy | Day | Los Angeles | F |
| 3 | Ashley | Ruiz | San Francisco | F |
| 4 | Stephanie | Gomez | Portland | F |

The `read_excel` function supports many of the same parameters as `read_csv`, including `index_col` to set the index columns, `usecols` to select the columns, and `squeeze` to coerce a one-column `DataFrame` into a `Series` object. The next example sets the City column as the index and keeps only three of the data set's four columns. Note that if we pass a column to the `index_col` parameter, we must also include the column in the `usecols` list:

```
In [27] pd.read_excel(
        io = "Single Worksheet.xlsx",
        usecols = ["City", "First Name", "Last Name"],
        index_col = "City"
    )
```

```
Out [27]
```

| City | First Name Last Name | | |
|---------------|----------------------|------------|-----------|
| | | First Name | Last Name |
| Miami | Brandon | James | |
| Denver | Sean | Hawkins | |
| Los Angeles | Judy | Day | |
| San Francisco | Ashley | Ruiz | |
| Portland | Stephanie | Gomez | |

The complexity increases slightly when a workbook contains multiple worksheets. The `Multiple Worksheets.xlsx` workbook holds three worksheets: Data 1, Data 2, and Data 3. By default, pandas imports only the first worksheet in the workbook:

```
In [28] pd.read_excel("Multiple Worksheets.xlsx")
Out [28]
```

| | First Name | Last Name | City | Gender |
|---|------------|-----------|---------------|--------|
| 0 | Brandon | James | Miami | M |
| 1 | Sean | Hawkins | Denver | M |
| 2 | Judy | Day | Los Angeles | F |
| 3 | Ashley | Ruiz | San Francisco | F |
| 4 | Stephanie | Gomez | Portland | F |

During import, pandas assigns each worksheet an index position starting at 0. We can import a specific worksheet by passing the worksheet's index position or its name to the `sheet_name` parameter. The parameter's default argument is 0 (the first worksheet). Therefore, the following two statements return the same DataFrame:

```
In [29] # The two lines below are equivalent
        pd.read_excel("Multiple Worksheets.xlsx", sheet_name = 0)
        pd.read_excel("Multiple Worksheets.xlsx", sheet_name = "Data 1")

Out [29]
```

| | First Name | Last Name | City | Gender |
|---|------------|-----------|---------------|--------|
| 0 | Brandon | James | Miami | M |
| 1 | Sean | Hawkins | Denver | M |
| 2 | Judy | Day | Los Angeles | F |
| 3 | Ashley | Ruiz | San Francisco | F |
| 4 | Stephanie | Gomez | Portland | F |

To import all worksheets, we can pass an argument of `None` to the `sheet_name` parameter. Pandas will store each worksheet in a separate DataFrame. The `read_excel` function returns a dictionary with the worksheets' names as keys and the respective DataFrames as values:

```
In [30] workbook = pd.read_excel(
        "Multiple Worksheets.xlsx", sheet_name = None
    )

workbook

Out [30] {'Data 1':   First Name Last Name      City Gender
          0    Brandon     James      Miami      M
          1      Sean    Hawkins     Denver      M
          2      Judy       Day  Los Angeles      F
          3    Ashley      Ruiz  San Francisco      F
          4  Stephanie    Gomez  Portland      F,
      'Data 2':   First Name Last Name      City Gender
          0    Parker     Power    Raleigh      F
          1  Preston  Prescott  Philadelphia      F
          2  Ronaldo  Donaldo      Bangor      M
          3    Megan    Stiller  San Francisco      M
          4   Bustin   Jieber      Austin      F,
      'Data 3':   First Name Last Name      City Gender
          0   Robert    Miller     Seattle      M
          1     Tara    Garcia    Phoenix      F
          2  Raphael Rodriguez    Orlando      M}
```

```
In [31] type(workbook)
```

```
Out [31] dict
```

To access a DataFrame/worksheet, we access a key in the dictionary. Here, we access the DataFrame for the Data 2 worksheet:

```
In [32] workbook["Data 2"]
```

```
Out [32]
```

| | First Name | Last Name | City | Gender |
|---|------------|-----------|---------------|--------|
| 0 | Parker | Power | Raleigh | F |
| 1 | Preston | Prescott | Philadelphia | F |
| 2 | Ronaldo | Donaldo | Bangor | M |
| 3 | Megan | Stiller | San Francisco | M |
| 4 | Bustin | Jieber | Austin | F |

To specify a subset of worksheets to import, we can pass the `sheet_name` parameter a list of index positions or worksheet names. Pandas still returns a dictionary. The dictionary's keys will match the strings in the `sheet_name` list. The next example imports only the Data 1 and Data 3 worksheets:

```
In [33] pd.read_excel(
        "Multiple Worksheets.xlsx",
        sheet_name = ["Data 1", "Data 3"]
    )
```

```
Out [33] {'Data 1':   First Name Last Name           City Gender
          0     Brandon      James       Miami      M
          1       Sean      Hawkins      Denver      M
          2       Judy       Day      Los Angeles      F
          3     Ashley      Ruiz      San Francisco      F
          4  Stephanie     Gomez      Portland      F,
'Data 3':   First Name Last Name           City Gender
          0     Robert      Miller      Seattle      M
          1       Tara      Garcia      Phoenix      F
          2   Raphael      Rodriguez      Orlando      M}
```

The next example targets index positions 1 and 2 or, equivalently, the second and third worksheets:

```
In [34] pd.read_excel("Multiple Worksheets.xlsx", sheet_name = [1, 2])
```

```
Out [34] {1:   First Name Last Name           City Gender
          0     Parker      Power      Raleigh      F
          1   Preston     Prescott      Philadelphia      F
          2   Ronaldo     Donaldo      Bangor      M
          3     Megan      Stiller      San Francisco      M
          4   Bustin      Jieber      Austin      F,
2:   First Name Last Name           City Gender
          0     Robert      Miller      Seattle      M
          1       Tara      Garcia      Phoenix      F
          2   Raphael      Rodriguez      Orlando      M}
```

After we've imported the DataFrame, we're free to invoke whatever methods we like on it. The original source of the data has no impact on our available operations.

12.3.3 Exporting Excel workbooks

Let's return to the baby_names DataFrame that we downloaded from the city of New York. Here's a reminder of what it looks like:

```
In [35] baby_names.head()
```

```
Out [35]
```

| | Year of Birth | Gender | Ethnicity | Child's First Name | Count | Rank |
|---|---------------|--------|-----------|--------------------|-------|------|
| 0 | 2011 | FEMALE | HISPANIC | GERALDINE | 13 | 75 |
| 1 | 2011 | FEMALE | HISPANIC | GIA | 21 | 67 |
| 2 | 2011 | FEMALE | HISPANIC | GIANNA | 49 | 42 |
| 3 | 2011 | FEMALE | HISPANIC | GISELLE | 38 | 51 |
| 4 | 2011 | FEMALE | HISPANIC | GRACE | 36 | 53 |

Let's say we want to split the data set into two DataFrames, one for each gender. Then we'd like to write each DataFrame to a separate worksheet in a new Excel workbook. We can begin by filtering the baby_names DataFrame, using the values in the Gender column. Chapter 5 introduced the following syntax:

```
In [36] girls = baby_names[baby_names["Gender"] == "FEMALE"]
boys = baby_names[baby_names["Gender"] == "MALE"]
```

Writing to an Excel workbook requires a few more steps than writing to a CSV. First up, we need to create an ExcelWriter object. This object serves as the foundation of the workbook. We'll attach individual worksheets to it in a moment.

The ExcelWriter constructor is available as a top-level attribute of the pandas library. Its first parameter, path, accepts the new workbook's filename as a string. If we do not provide a path to a directory, pandas will create the Excel file in the same directory as the Jupyter Notebook. Make sure to save the ExcelWriter object to a variable. The following example uses excel_file:

```
In [37] excel_file = pd.ExcelWriter("Baby_Names.xlsx")
excel_file
```

```
Out [37] <pandas.io.excel._openpyxl._OpenpyxlWriter at 0x118a7bf90>
```

Next, we need to connect our girls and boys DataFrames to individual worksheets in the workbook. Let's start with the former.

A DataFrame includes a to_excel method for writing to an Excel workbook. The method's first parameter, excel_writer, accepts an ExcelWriter object, like the one we created in the preceding example. The method's sheet_name parameter accepts the worksheet name as a string. Finally, we can pass the index parameter a value of False to exclude the DataFrame index:

```
In [38] girls.to_excel(
        excel_writer = excel_file, sheet_name = "Girls", index = False
    )
```

Note that we have not created the Excel workbook yet. Rather, we've wired up the `ExcelWriter` object to include the girls `DataFrame` when we do create the workbook.

Next, let's connect our boys `DataFrame` to the Excel workbook. We'll invoke the `to_excel` method on `boys`, passing the `excel_writer` parameter the same `ExcelWriter` object. Now pandas knows that it should write both data sets to the same workbook. Let's also alter the string argument to the `sheet_name` parameter. To export only a subset of columns, let's pass a custom list to the `columns` parameter. The next example instructs pandas to include only the Child's First Name, Count, and Rank columns when writing the boys `DataFrame` to the "Boys" worksheet in the workbook:

```
In [39] boys.to_excel(
    excel_file,
    sheet_name = "Boys",
    index = False,
    columns = ["Child's First Name", "Count", "Rank"]
)
```

Now that we've configured the Excel workbook's plumbing, we're clear to write it to disk. Invoke the `save` method on the `excel_file` `ExcelWriter` object to complete the process:

```
In [40] excel_file.save()
```

| | |
|--------------------------|--|
| <input type="checkbox"/> | Chapter 12 - Imports and Exports.ipynb |
| <input type="checkbox"/> | Baby_Names.xlsx |

Figure 12.5 The XLSX Excel file saved to the same directory as the Jupyter Notebook

Check out the Jupyter Notebook interface to see the result. Figure 12.5 shows the new `Baby_Names.xlsx` file in the same folder.

And there you have it. Now you know how to export

JSON, CSV, and XLSX files from pandas. The library offers additional functions for exporting its data structures to other file formats.

12.4 Coding challenge

Let's practice the concepts introduced in this chapter. The `tv_shows.json` file is an aggregate collection of TV show episodes pulled from the `Episodate.com API` (see <https://www.episodate.com/api>). The JSON includes data for three TV shows: *The X-Files*, *Lost*, and *Buffy the Vampire Slayer*.

```
In [41] tv_shows_json = pd.read_json("tv_shows.json")
tv_shows_json
```

```
Out [41]
```

| shows |
|---|
| 0 {'show': 'The X-Files', 'runtime': 60, 'network': 'FOX', ...} |
| 1 {'show': 'Lost', 'runtime': 60, 'network': 'ABC', 'episo...} |
| 2 {'show': 'Buffy the Vampire Slayer', 'runtime': 60, 'net...} |

The JSON consists of a top-level "shows" key that connects to a list of three dictionaries, one for each of the three shows:

```
{  
    "shows": [{}], {}]  
}
```

Each nested show dictionary includes "show", "runtime", "network", and "episodes" keys. Here's a truncated preview of the first row's dictionary:

```
In [42]: tv_shows_json.loc[0, "shows"]  
  
Out [42]: {'show': 'The X-Files',  
           'runtime': 60,  
           'network': 'FOX',  
           'episodes': [{  
               'season': 1,  
               'episode': 1,  
               'name': 'Pilot',  
               'air_date': '1993-09-11 01:00:00'},  
              {  
               'season': 1,  
               'episode': 2,  
               'name': 'Deep Throat',  
               'air_date': '1993-09-18 01:00:00'}]}
```

The "episodes" key maps to a list of dictionaries. Each dictionary holds data for one show episode. In the previous example, we see the data for the first two episodes of season 1 of *The X-Files*.

12.4.1 Problems

Your challenges are

- 1 Normalize the nested episode data for each dictionary in the shows column. The goal is a DataFrame with a separate row for each episode. Each row should include the episode's relevant metadata (season, episode, name, and air_date) as well as the show's top-level information (show, runtime, and network).
- 2 Filter the normalized data set into three separate DataFrames, one for each of the shows ("The X-Files", "Lost", and "Buffy the Vampire Slayer").
- 3 Write the three DataFrames to an episodes.xlsx Excel workbook, and save each TV show's episode data to a separate worksheet. (The worksheet names are up to you.)

12.4.2 Solutions

Let's tackle the problems:

- 1 We can use the json_normalize function to extract each TV show's nested batch of episodes. The episodes are available under the "episodes" key, which we can pass to the method's record_path parameter. To preserve the top-level show data, we can pass the meta parameter a list of the top-level keys to keep:

```
In [43] tv_shows = pd.json_normalize(
    data = tv_shows_json["shows"],
    record_path = "episodes",
    meta = ["show", "runtime", "network"]
)

tv_shows

Out [43]
```

| season | episode | name | air_date | show | runtime | network |
|--------|---------|--------------|--------------|--------------|---------|---------|
| 0 | 1 | Pilot | 1993-09-1... | The X-Files | 60 | FOX |
| 1 | 1 | Deep Throat | 1993-09-1... | The X-Files | 60 | FOX |
| 2 | 1 | Squeeze | 1993-09-2... | The X-Files | 60 | FOX |
| 3 | 1 | Conduit | 1993-10-0... | The X-Files | 60 | FOX |
| 4 | 1 | The Jerse... | 1993-10-0... | The X-Files | 60 | FOX |
| ... | ... | ... | ... | ... | ... | ... |
| 477 | 7 | Dirty Girls | 2003-04-1... | Buffy the... | 60 | UPN |
| 478 | 7 | Empty Places | 2003-04-3... | Buffy the... | 60 | UPN |
| 479 | 7 | Touched | 2003-05-0... | Buffy the... | 60 | UPN |
| 480 | 7 | End of Days | 2003-05-1... | Buffy the... | 60 | UPN |
| 481 | 7 | Chosen | 2003-05-2... | Buffy the... | 60 | UPN |

482 rows × 7 columns

- 2 Our next challenge is to split the data set into three `DataFrames`, one for each TV show. We can filter the rows in `tv_shows` based on the values in the `show` column:

```
In [44] xfiles = tv_shows[tv_shows["show"] == "The X-Files"]
lost = tv_shows[tv_shows["show"] == "Lost"]
buffy = tv_shows[tv_shows["show"] == "Buffy the Vampire Slayer"]
```

- 3 Finally, let's write the three `DataFrames` to an Excel workbook. We'll begin by instantiating an `ExcelWriter` object and saving it to a variable. We can pass in the workbook name as the first argument. I've chosen to call it `episodes.xlsx`:

```
In [45] episodes = pd.ExcelWriter("episodes.xlsx")
episodes

Out [45] <pandas.io.excel._openpyxl._OpenpyxlWriter at 0x11e5cd3d0>
```

Next, we must invoke the `to_excel` method on the three `DataFrames` to connect them to individual worksheets in the workbook. We'll pass the same `episodes` `ExcelWriter` object to the `excel_writer` parameter in each invocation. We'll make sure to provide a unique name for each worksheet via the `sheet_name` parameter. Finally, we'll pass the `index` parameter a value of `False` to exclude the `DataFrame` index:

```
In [46] xfiles.to_excel(
    excel_writer = episodes, sheet_name = "X-Files", index = False
)
```

```
In [47]: lost.to_excel(  
                      excel_writer = episodes, sheet_name = "Lost", index = False  
                  )  
  
In [48]: buffy.to_excel(  
                      excel_writer = episodes,  
                      sheet_name = "Buffy the Vampire Slayer",  
                      index = False  
                  )
```

With the worksheets wired up, we can invoke the `save` method on the `episodes` `ExcelWriter` object to create the `episodes.xlsx` workbook:

```
In [49]: episodes.save()
```

Congratulations on completing the coding challenge!

Summary

- The `read_json` function parses a JSON file into a `DataFrame`.
- The `json_normalize` function converts nested JSON data to a tabular `Data-Frame`.
- We can pass URLs to import functions such as `read_csv`, `read_json`, and `read_excel`. Pandas will download the data set from the provided link.
- The `read_excel` function imports an Excel workbook. The method's `sheet_name` parameter sets the worksheets to import. When we import multiple worksheets, pandas stores the resulting `DataFrames` in a dictionary.
- To write one or more `DataFrames` to an Excel workbook, instantiate an `ExcelWriter` object, attach the `DataFrames` to it via the `to_excel` method, and then invoke the `save` method on the `ExcelWriter` object.

13

Configuring pandas

This chapter covers

- Configuring pandas display settings for both the Notebook and single cells
- Limiting the number of printed `DataFrame` rows and columns
- Altering the precision of decimal-point numbers
- Truncating a cell's text content
- Rounding numeric values when they fall below a floor

As we've worked through the book's data sets, we've seen how pandas improves our user experience by making sensible decisions on data presentation. When we output a 1,000-row `DataFrame`, for example, the library assumes that we'd prefer to see 30 rows from the beginning and end rather than the whole data set, which can clutter the screen. Sometimes, we may want to break from pandas' assumptions and alter its settings to fit our custom display needs. Luckily, the library exposes many of its internal settings for us to alter. In this chapter, we'll learn how to configure options such as row and column limits, floating-point precision, and value rounding. Let's get our hands dirty and see how we can switch things up.

13.1 Getting and setting pandas options

We'll begin by importing the pandas library and assigning it an alias of pd:

```
In [1] import pandas as pd
```

This chapter's data set, `happiness.csv`, is a ranking of the world's nations by happiness. The polling firm Gallup gathers the data with support from the United Nations. Each row includes a nation's aggregate happiness score alongside individual scores for gross domestic product (GDP) per capita, social support, life expectancy, and generosity. The data set holds 6 columns and 156 rows:

```
In [2] happiness = pd.read_csv("happiness.csv")
       happiness.head()
```

```
Out [2]
```

| | Country | Score | GDP per cap... | Social sup... | Life expect... | Generosity |
|---|-------------|-------|----------------|---------------|----------------|------------|
| 0 | Finland | 7.769 | 1.340 | 1.587 | 0.986 | 0.153 |
| 1 | Denmark | 7.600 | 1.383 | 1.573 | 0.996 | 0.252 |
| 2 | Norway | 7.554 | 1.488 | 1.582 | 1.028 | 0.271 |
| 3 | Iceland | 7.494 | 1.380 | 1.624 | 1.026 | 0.354 |
| 4 | Netherlands | 7.488 | 1.396 | 1.522 | 0.999 | 0.322 |

Pandas stores its settings in a single `options` object at the top level of the library. Each option belongs to a parent category. Let's start with the `display` category, which holds settings for the printed representation of pandas' data structures.

The top-level `describe_option` function returns the documentation for a given setting. We can pass it a string with the setting's name. Let's look into the `max_rows` option, which is nested within the `display` parent category. The `max_rows` setting configures the maximum number of rows that pandas prints before it truncates a `DataFrame`:

```
In [3] pd.describe_option("display.max_rows")
```

```
Out [3]
```

```
display.max_rows : int
    If max_rows is exceeded, switch to truncate view. Depending on
    'large_repr', objects are either centrally truncated or printed
    as a summary view. 'None' value means unlimited.

    In case python/IPython is running in a terminal and
    'large_repr' equals 'truncate' this can be set to 0 and pandas
    will auto-detect the height of the terminal and print a
    truncated object which fits the screen height. The IPython
    notebook, IPython qtconsole, or IDLE do not run in a terminal
    and hence it is not possible to do correct auto-detection.

    [default: 60] [currently: 60]
```

Notice that the end of the documentation includes the setting's default value and its current value.

Pandas will print all library options that match the string argument. The library uses regular expressions to compare `describe_option`'s argument with its available settings. As a reminder, a *regular expression* is a search pattern for text; see appendix E for a detailed overview. The next example passes an argument of "max_col". Pandas prints documentation for the two settings that match the term:

```
In [4] pd.describe_option("max_col")  
Out [4]  
  
display.max_columns : int  
    If max_cols is exceeded, switch to truncate view. Depending on  
    `large_repr`, objects are either centrally truncated or printed as  
    a summary view. 'None' value means unlimited.  
  
    In case python/IPython is running in a terminal and `large_repr`  
    equals 'truncate' this can be set to 0 and pandas will auto-detect  
    the width of the terminal and print a truncated object which fits  
    the screen width. The IPython notebook, IPython qtconsole, or IDLE  
    do not run in a terminal and hence it is not possible to do  
    correct auto-detection.  
    [default: 20] [currently: 5]  
display.max_colwidth : int or None  
    The maximum width in characters of a column in the repr of  
    a pandas data structure. When the column overflows, a "..."  
    placeholder is embedded in the output. A 'None' value means unlimited.  
    [default: 50] [currently: 9]
```

Although regular expressions are appealing, I recommend writing out the full name of the setting, including its parent category. Explicit code tends to lead to fewer errors.

There are two ways to get a setting's current value. The first way is the `get_option` function at the top level of pandas; like `describe_option`, it accepts a string argument with the setting's name. The second approach is to access the parent category and the specific setting as attributes on the top-level `pd.options` object.

The following example shows the syntax for both strategies. Both lines of code return 60 for the `max_rows` setting, which means that pandas will truncate any Data-Frame output greater than 60 rows in length:

```
In [5] # The two lines below are equivalent  
      pd.get_option("display.max_rows")  
      pd.options.display.max_rows  
  
Out [5] 60
```

Similarly, there are two ways to *set* a new value for a configuration setting. The `set_option` function at the top level of pandas accepts the setting as its first argument and its new value as the second argument. Alternatively, we can access the option via attributes on the `pd.options` object and assign the new value with an equal sign:

```
In [6] # The two lines below are equivalent  
      pd.set_option("display.max_rows", 6)  
      pd.options.display.max_rows = 6
```

We've instructed pandas to truncate the DataFrame output if it is longer than six rows:

```
In [7] pd.options.display.max_rows
```

```
Out [7] 6
```

Let's see the change in action. The next example asks pandas to print the first six rows of happiness. The threshold of six maximum rows is not crossed, so pandas outputs the DataFrame without truncation:

```
In [8] happiness.head(6)
```

```
Out [8]
```

| | Country | Score | GDP per cap... | Social sup... | Life expect... | Generosity |
|---|-------------|-------|----------------|---------------|----------------|------------|
| 0 | Finland | 7.769 | 1.340 | 1.587 | 0.986 | 0.153 |
| 1 | Denmark | 7.600 | 1.383 | 1.573 | 0.996 | 0.252 |
| 2 | Norway | 7.554 | 1.488 | 1.582 | 1.028 | 0.271 |
| 3 | Iceland | 7.494 | 1.380 | 1.624 | 1.026 | 0.354 |
| 4 | Netherlands | 7.488 | 1.396 | 1.522 | 0.999 | 0.322 |
| 5 | Switzerland | 7.480 | 1.452 | 1.526 | 1.052 | 0.263 |

Now let's cross the threshold and ask pandas to print the first seven rows of happiness. The library always aims to print an equal number of rows before and after the truncation. In the next example, it prints three rows from the beginning of the output and three rows from the end of the output, truncating the middle row (index 3):

```
In [9] happiness.head(7)
```

```
Out [9]
```

| | Country | Score | GDP per cap... | Social sup... | Life expect... | Generosity |
|-----|-------------|-------|----------------|---------------|----------------|------------|
| 0 | Finland | 7.769 | 1.340 | 1.587 | 0.986 | 0.153 |
| 1 | Denmark | 7.600 | 1.383 | 1.573 | 0.996 | 0.252 |
| 2 | Norway | 7.554 | 1.488 | 1.582 | 1.028 | 0.271 |
| ... | ... | ... | ... | ... | ... | ... |
| 4 | Netherlands | 7.488 | 1.396 | 1.522 | 0.999 | 0.322 |
| 5 | Switzerland | 7.480 | 1.452 | 1.526 | 1.052 | 0.263 |
| 6 | Sweden | 7.343 | 1.387 | 1.487 | 1.009 | 0.267 |

```
7 rows × 6 columns
```

The `max_rows` setting declares the number of printed rows. The complementary `display.max_columns` option sets the maximum number of printed columns. The default value is 20:

```
In [10] # The two lines below are equivalent
pd.get_option("display.max_columns")
pd.options.display.max_columns
```

```
Out [10] 20
```

Again, to assign a new value, we can use the `set_option` function or access the nested `max_columns` attribute directly:

```
In [11] # The two lines below are equivalent
pd.set_option("display.max_columns", 2)
pd.options.display.max_columns = 2
```

If we set an even number of max columns, pandas will exclude the truncation column from its max column count. The happiness DataFrame has six columns, but the following output displays only two of them. Pandas includes the first and last columns, Country and Generosity, and places a truncation column between the two:

```
In [12] happiness.head(7)
```

```
Out [12]
```

| | Country | ... | Generosity |
|-----|----------------|-----|-------------------|
| 0 | Finland | | 0.153 |
| 1 | Denmark | ... | 0.252 |
| 2 | Norway | ... | 0.271 |
| ... | ... | ... | ... |
| 4 | Netherlands | ... | 0.322 |
| 5 | Switzerland | ... | 0.263 |
| 6 | Sweden | ... | 0.267 |

```
7 rows × 6 columns
```

If we set an odd number of max columns, pandas will include the truncation column in its column count. An odd number ensures that pandas can pack an equal number of columns on both sides of the truncation. The next example sets the `max_columns` value to 5. The happiness output displays the two leftmost columns (Country and Score), the truncation column, and the two rightmost columns (Life expectancy and Generosity). Pandas prints four of the original six columns:

```
In [13] # The two lines below are equivalent
pd.set_option("display.max_columns", 5)
pd.options.display.max_columns = 5
```

```
In [14] happiness.head(7)
```

```
Out [14]
```

| | Country | Score | ... | Life expectancy | Generosity |
|-----|----------------|--------------|-----|------------------------|-------------------|
| 0 | Finland | 7.769 | ... | 0.986 | 0.153 |
| 1 | Denmark | 7.600 | ... | 0.996 | 0.252 |
| 2 | Norway | 7.554 | ... | 1.028 | 0.271 |
| ... | ... | ... | ... | ... | ... |
| 4 | Netherlands | 7.488 | ... | 0.999 | 0.322 |
| 5 | Switzerland | 7.480 | ... | 1.052 | 0.263 |
| 6 | Sweden | 7.343 | ... | 1.009 | 0.267 |

```
5 rows × 6 columns
```

To return a setting to its original value, pass its name to the `reset_option` function at the top level of pandas. The next example resets the `max_rows` setting:

```
In [15]: pd.reset_option("display.max_rows")
```

We can confirm the change by invoking the `get_option` function again:

```
In [16]: pd.get_option("display.max_rows")
```

```
Out [16]: 60
```

Pandas has reset the `max_rows` setting to its default value of 60.

13.2 Precision

Now that we're comfortable with pandas' API for changing settings, let's walk through a few popular configuration options.

The `display.precision` option sets the number of digits after a floating-point number. The default value is 6:

```
In [17]: pd.describe_option("display.precision")
```

```
Out [17]
```

```
display.precision : int
    Floating point output precision (number of significant
    digits). This is only a suggestion
    [default: 6] [currently: 6]
```

The next example sets the precision to 2. The setting affects values in all four of the floating-point columns in `happiness`:

```
In [18]: # The two lines below are equivalent
pd.set_option("display.precision", 2)
pd.options.display.precision = 2
```

```
In [19]: happiness.head()
```

```
Out [19]
```

| | Country | Score | ... | Life expectancy | Generosity |
|---|-------------|-------|-----|-----------------|------------|
| 0 | Finland | 7.77 | ... | 1.34 | 0.15 |
| 1 | Denmark | 7.60 | ... | 1.38 | 0.25 |
| 2 | Norway | 7.55 | ... | 1.49 | 0.27 |
| 3 | Iceland | 7.49 | ... | 1.38 | 0.35 |
| 4 | Netherlands | 7.49 | ... | 1.40 | 0.32 |

```
5 rows × 6 columns
```

The `precision` setting alters only the presentation of floating-point numbers. Pandas preserves the original values within the DataFrame, which we can prove by using the `loc` accessor to extract a sample value from a floating-point column like `Score`:

```
In [20]: happiness.loc[0, "Score"]
```

```
Out [20]: 7.769
```

The Score column's original value, 7.769, is still present. Pandas changes the presentation of the value to 7.77 when it prints the DataFrame.

13.3 Maximum column width

The `display.max_colwidth` setting sets the maximum number of characters pandas prints before truncating a cell's text:

```
In [21] pd.describe_option("display.max_colwidth")
```

```
Out [21]
```

```
display.max_colwidth : int or None
    The maximum width in characters of a column in the repr of
    a pandas data structure. When the column overflows, a "...""
    placeholder is embedded in the output. A 'None' value means
    unlimited.
[default: 50] [currently: 50]
```

The next example asks pandas to truncate text if its length is greater than nine characters:

```
In [22] # The two lines below are equivalent
        pd.set_option("display.max_colwidth", 9)
        pd.options.display.max_colwidth = 9
```

Let's see what happens when we output happiness:

```
In [23] happiness.tail()
```

```
Out [23]
```

| | Country | Score | ... | Life expectancy | Generosity |
|-----|----------------|--------------|-----|------------------------|-------------------|
| 151 | Rwanda | 3.33 | ... | 0.61 | 0.22 |
| 152 | Tanzania | 3.23 | ... | 0.50 | 0.28 |
| 153 | Afgha... | 3.20 | ... | 0.36 | 0.16 |
| 154 | Central Afr... | 3.08 | ... | 0.10 | 0.23 |
| 155 | South... | 2.85 | ... | 0.29 | 0.20 |

5 rows × 6 columns

Pandas shortens the last three Country values (Afghanistan, Central African Republic, and South Sudan). The first two values in the output (Rwanda at six characters and Tanzania at eight characters) remain unaffected.

13.4 Chop threshold

In some analyses, we may consider values to be insignificant if they are reasonably close to 0. Your business domain, for example, may consider the value 0.10 to be “as good as 0” or “effectively 0”. The `display.chop_threshold` option sets the floor that a floating-point value must cross to be printed. Pandas will display any value below the threshold as 0:

```
In [24] pd.describe_option("display.chop_threshold")
Out [24]

display.chop_threshold : float or None
    if set to a float value, all float values smaller than the
    given threshold will be displayed as exactly 0 by repr and
    friends.
[default: None] [currently: None]
```

This example sets 0.25 as the chop threshold:

```
In [25] pd.set_option("display.chop_threshold", 0.25)
```

In the next output, notice that pandas prints the values in the Life expectancy and Generosity columns for index 154 (0.105 and 0.235, respectively) as 0.00 in the output:

```
In [26] happiness.tail()
```

```
Out [26]
```

| | Country | Score | ... | Life expectancy | Generosity |
|-----|----------------|-------|-----|-----------------|------------|
| 151 | Rwanda | 3.33 | ... | 0.61 | 0.00 |
| 152 | Tanzania | 3.23 | ... | 0.50 | 0.28 |
| 153 | Afghanistan | 3.20 | ... | 0.36 | 0.00 |
| 154 | Central Afr... | 3.08 | ... | 0.00 | 0.00 |
| 155 | South Sudan | 2.85 | ... | 0.29 | 0.00 |

5 rows × 6 columns

Much like the precision setting, `chop_threshold` does not change the underlying values in the DataFrame—only their printed representation.

13.5 Option context

The settings we've altered so far have been global. When we change them, we alter the output of all Jupyter Notebook cells executed afterward. A global setting persists until we assign a new value to it. If we set `display.max_columns` to 6, for example, Jupyter will output DataFrames with a maximum of six columns for all future cell executions.

Sometimes, we want to customize presentation options for a single cell. We can accomplish this task with pandas' top-level `option_context` function. We pair the function with Python's built-in `with` keyword to create a context block. Think of a *context block* as being a temporary execution environment. The `option_context` function sets temporary values for pandas options while the code inside the block executes; global pandas settings are not affected.

We pass settings to the `option_context` function as sequential arguments. The next example prints the `happiness` DataFrame with

- `display.max_columns` set to 5
- `display.max_rows` set to 10
- `display.precision` set to 3

Jupyter does not recognize the `with` block's contents as the final statement of a Notebook cell. Thus, we need to use a Notebook function called `display` to output the `DataFrame` manually:

```
In [27]: with pd.option_context(
    "display.max_columns", 5,
    "display.max_rows", 10,
    "display.precision", 3
):
    display(happiness)

Out [27]:
   Country  Score  ...  Life expectancy  Generosity
0    Finland  7.769  ...          0.986      0.153
1   Denmark  7.600  ...          0.996      0.252
2    Norway  7.554  ...          1.028      0.271
3    Iceland  7.494  ...          1.026      0.354
4  Netherlands  7.488  ...          0.999      0.322
...
151      Rwanda  3.334  ...          0.614      0.217
152    Tanzania  3.231  ...          0.499      0.276
153  Afghanistan  3.203  ...          0.361      0.158
154  Central Afr...  3.083  ...          0.105      0.235
155  South Sudan  2.853  ...          0.295      0.202

156 rows × 6 columns
```

Because we used the `with` keyword, we did not alter global Notebook settings for these three options; they retain their original values.

The `option_context` function is helpful for assigning different options to different cell executions. If you'd like a uniform presentation for all output, I recommend setting the options once in a cell at the top of your Jupyter Notebook.

Summary

- The `describe_option` function returns documentation for a pandas setting.
- The `set_option` function sets a new value for a setting.
- We can also change a setting by accessing and overwriting attributes on the `pd.options` object.
- The `reset_option` function changes a pandas setting back to its default value.
- The `display.max_rows` and `display.max_columns` options set the maximum rows/columns that pandas shows in the output.
- The `display.precision` setting alters the number of digits after a decimal point.
- The `display.max_colwidth` option sets the numeric threshold at which pandas truncates printed characters.
- The `display.chop_threshold` option sets a numeric floor. If values do not cross the threshold, pandas will print them as zeroes.
- Pair the `option_context` function and the `with` keyword to create a temporary execution context for a block completely.

14

Visualization

This chapter covers

- Installing the Matplotlib library for data visualization
- Rendering graphs and charts with pandas and Matplotlib
- Applying color templates to visualizations

Text-based DataFrame summaries are helpful, but many times, a story can best be told by a visualization. A line chart can quickly communicate a trend over time; a bar graph can distinctly identify unique categories and their counts; a pie chart can represent proportions in an easily digestible manner, and so on. Fortunately, pandas seamlessly integrates with many popular Python data visualization libraries, including Matplotlib, seaborn, and ggplot. In this chapter, we'll learn how to use Matplotlib to render dynamic charts from our Series and DataFrames. I hope that these visualizations help you add that little spark to your data presentations.

14.1 Installing matplotlib

By default, pandas relies on the open source Matplotlib package to render charts and graphs. Let's install it in our Anaconda environment.

Begin by launching the Terminal (macOS) or Anaconda Prompt (Windows) application for your operating system. The default Anaconda environment, `base`, should be listed in parentheses to the left. `base` is the currently active environment.

When we installed Anaconda (see appendix A), we created an environment called `pandas_in_action`. Let's execute the `conda activate` command to activate it. If you chose a different environment name, replace `pandas_in_action` with that name, as follows:

```
(base) ~$ conda activate pandas_in_action
```

The parentheses should change to reflect the active environment. Execute the command `conda install matplotlib` to install the Matplotlib library within the `pandas_in_action` environment:

```
(pandas_in_action) ~$ conda install matplotlib
```

When the prompt asks you to confirm, enter '`Y`' for yes and press Enter. When installation completes, execute `jupyter notebook` and create a new Notebook.

14.2 Line charts

As always, let's begin by importing the `pandas` library. We'll also import the `pyplot` package from within the Matplotlib library. In this context, a *package* means a nested folder within the top library. We can access the `pyplot` package using dot syntax, the same way we access any library attribute. A common community alias for `pyplot` is `plt`.

By default, Jupyter Notebook renders each Matplotlib visualization in a separate browser window, like a pop-up window on a website. The windows can be a bit jarring, especially when there are multiple charts on the screen. We can add an extra line—`%matplotlib inline`—to force Jupyter to render visualizations directly below the code in a cell. `%matplotlib inline` is an example of a magic function, a syntactical shortcut for setting a configuration option in the Notebook:

```
In [1] import pandas as pd  
      import matplotlib.pyplot as plt  
      %matplotlib inline
```

Now on to the data! This chapter's data set, `space_missions.csv`, includes more than 100 space flights throughout 2019 and 2020. Each record consists of a mission's date, sponsoring company, location, cost, and status ("Success" or "Failure"):

```
In [2] pd.read_csv("space_missions.csv").head()  
Out [2]
```

| | Date | Company | Name | Location | Cost | Status |
|---|---------|-------------|--------|----------|--------|---------|
| 0 | 2/5/19 | Arianespace | | France | 200.00 | Success |
| 1 | 2/22/19 | | SpaceX | USA | 50.00 | Success |
| 2 | 3/2/19 | | SpaceX | USA | 50.00 | Success |
| 3 | 3/9/19 | | CASC | China | 29.15 | Success |
| 4 | 3/22/19 | Arianespace | | France | 37.00 | Success |

Let's adjust two settings before we assign the imported DataFrame to a space variable. First, we'll use the `parse_dates` parameter to import the values in the Date column as datetimes. Next, we'll set the Date column as the index of the DataFrame:

```
In [3] space = pd.read_csv(
        "space_missions.csv",
        parse_dates = ["Date"],
        index_col = "Date"
    )

space.head()
```

Out [3]

| | Company | Name | Location | Cost | Status |
|------------|-------------|--------|----------|--------|---------|
| Date | | | | | |
| 2019-02-05 | Arianespace | | France | 200.00 | Success |
| 2019-02-22 | | SpaceX | USA | 50.00 | Success |
| 2019-03-02 | | SpaceX | USA | 50.00 | Success |
| 2019-03-09 | | CASC | China | 29.15 | Success |
| 2019-03-22 | Arianespace | | France | 37.00 | Success |

Suppose that we want to plot the flight costs over the two years in this data set. A *time-series* graph is an optimal chart for observing a trend over time. We can plot time on the x-axis and values on the y-axis. First, let's extract the Cost column from the space DataFrame. The result is a Series with numeric values and a datetime index:

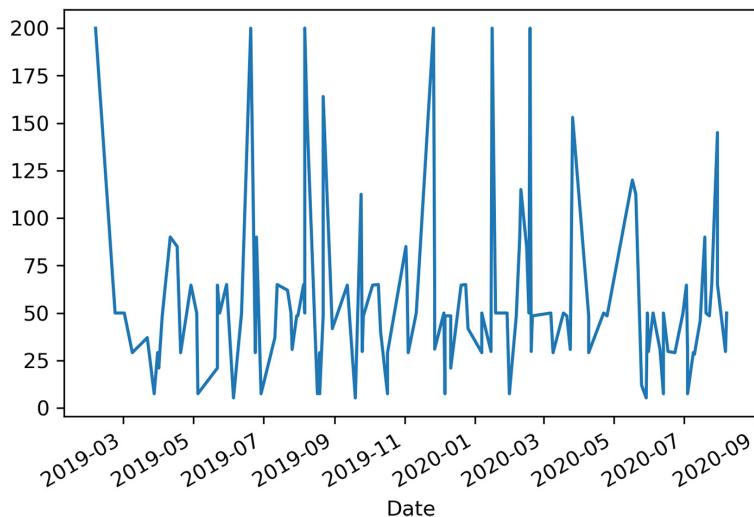
```
In [4] space["Cost"].head()

Out [4] Date
2019-02-05    200.00
2019-02-22     50.00
2019-03-02     50.00
2019-03-09     29.15
2019-03-22     37.00
Name: Cost, dtype: float64
```

To render a visualization, invoke the `plot` method on a pandas data structure. By default, Matplotlib draws a line graph. Jupyter also prints the location of the graph object in the computer's memory. The location will be different with each cell execution, so feel free to ignore it:

```
In [5] space["Cost"].plot()

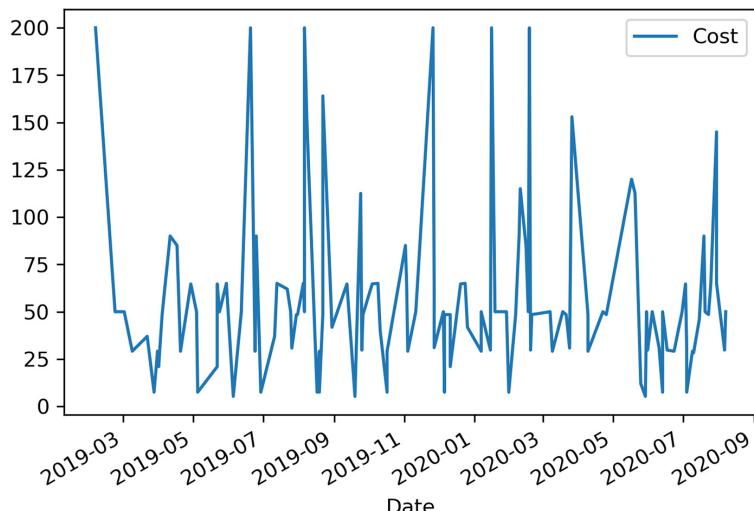
Out [5] <matplotlib.axes._subplots.AxesSubplot at 0x11e1c4650>
```



Pretty fancy! We have rendered a line chart with Matplotlib using values from pandas. By default, the library plots the index labels (in this case, the datetimes) on the x-axis and the Series' values on the y-axis. Matplotlib also calculates reasonable intervals for the range of values on both axes.

We can also invoke the `plot` method on the space DataFrame itself. In this scenario, pandas produces the same output, but only because the data set has only one numeric column:

```
In [6] space.plot()  
Out [6] <matplotlib.axes._subplots.AxesSubplot at 0x11ea18790>
```



If a DataFrame holds multiple numeric columns, Matplotlib will draw a separate line for each one. Be careful: if there is a large gap in the magnitude of values between columns (if one numeric column has values in the millions and another has values in the hundreds, for example), the larger values can easily dwarf the smaller ones. Consider this DataFrame:

```
In [7] data = [
    [2000, 3000000],
    [5000, 5000000]
]

df = pd.DataFrame(data = data, columns = ["Small", "Large"])
df

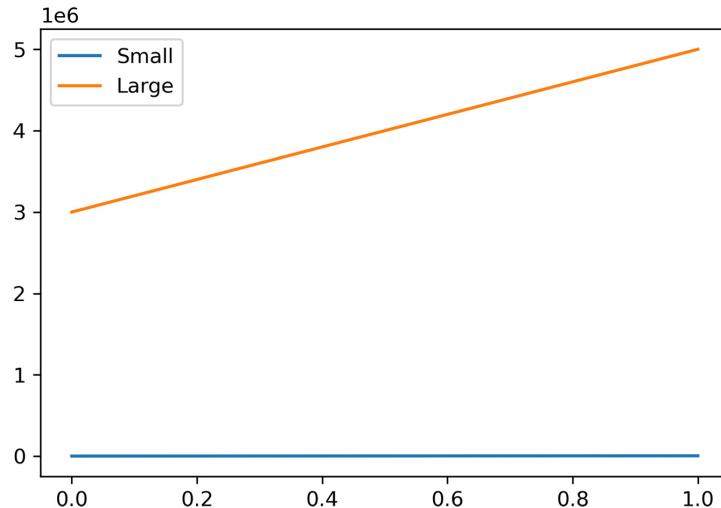
Out [7]
```

| | Small | Large |
|---|-------|---------|
| 0 | 2000 | 3000000 |
| 1 | 5000 | 5000000 |

When we plot the df DataFrame, Matplotlib adjusts the graph scale to accommodate the Large column's values. The trend in the Small column's values becomes impossible to see:

```
In [8] df.plot()

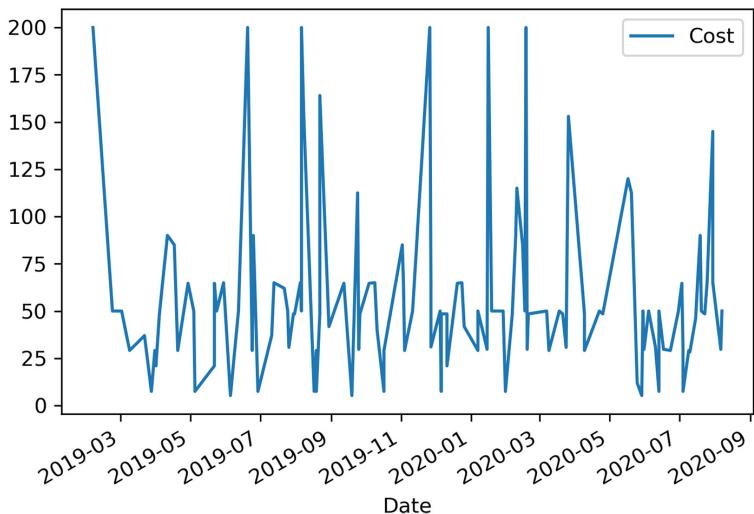
Out [8] <matplotlib.axes._subplots.AxesSubplot at 0x7fc48279b6d0>
```



Let's come back to space. The plot method accepts a y parameter to identify the DataFrame column whose values Matplotlib should plot. The next example passes the Cost column and is another way to render the same time-series graph:

```
In [9] space.plot(y = "Cost")
```

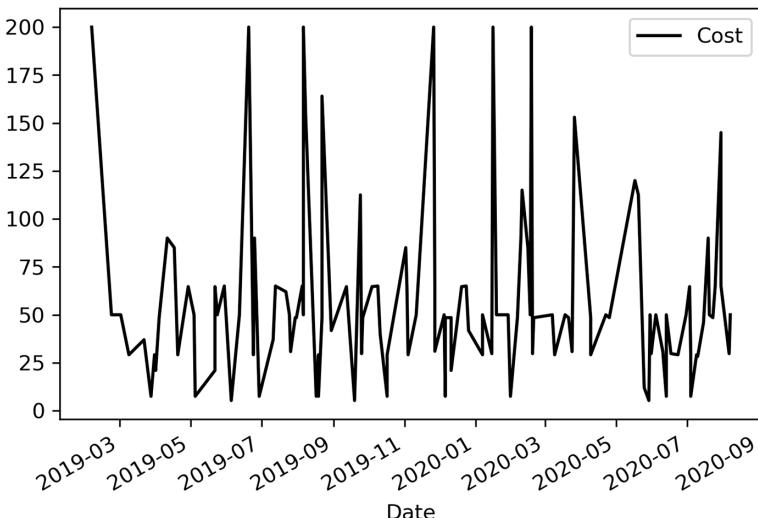
```
Out [9] <matplotlib.axes._subplots.AxesSubplot at 0x11eb0b990>
```



We can use the `colormap` parameter to alter the aesthetics of the visualization. Think of this process as setting the color theme of the graph. The parameter accepts a string with a predefined color palette from the Matplotlib library. The following example uses a "gray" theme that renders the line chart in black and white:

```
In [10] space.plot(y = "Cost", colormap = "gray")
```

```
Out [10] <matplotlib.axes._subplots.AxesSubplot at 0x11ebef350>
```



To see a list of valid inputs for the `colormaps` parameter, invoke the `colormaps` method on the `pyplot` library (aliased to `plt` in our Notebook). Note that we can apply some of these themes only if certain criteria are met, such as a minimum number of graph lines:

```
In [11] print(plt.colormaps())
```

```
Out [11] ['Accent', 'Accent_r', 'Blues', 'Blues_r', 'BrBG', 'BrBG_r',
          'BuGn', 'BuGn_r', 'BuPu', 'BuPu_r', 'CMRmap', 'CMRmap_r',
          'Dark2', 'Dark2_r', 'GnBu', 'GnBu_r', 'Greens', 'Greens_r',
          'Greys', 'Greys_r', 'OrRd', 'OrRd_r', 'Oranges', 'Oranges_r',
          'PRGn', 'PRGn_r', 'Paired', 'Paired_r', 'Pastell1', 'Pastell1_r',
          'Pastel2', 'Pastel2_r', 'PiYG', 'PiYG_r', 'PuBu', 'PuBuGn',
          'PuBuGn_r', 'PuBu_r', 'PuOr', 'PuOr_r', 'PuRd', 'PuRd_r',
          'Purples', 'Purples_r', 'RdBu', 'RdBu_r', 'RdGy', 'RdGy_r',
          'RdPu', 'RdPu_r', 'RdYlBu', 'RdYlBu_r', 'RdYlGn', 'RdYlGn_r',
          'Reds', 'Reds_r', 'Set1', 'Set1_r', 'Set2', 'Set2_r', 'Set3',
          'Set3_r', 'Spectral', 'Spectral_r', 'Wistia', 'Wistia_r', 'YlGn',
          'YlGnBu', 'YlGnBu_r', 'YlGn_r', 'YlOrBr', 'YlOrBr_r', 'YlOrRd',
          'YlOrRd_r', 'afmhot', 'afmhot_r', 'autumn', 'autumn_r', 'binary',
          'binary_r', 'bone', 'bone_r', 'brg', 'brg_r', 'bwr', 'bwr_r',
          'cividis', 'cividis_r', 'cool', 'cool_r', 'coolwarm',
          'coolwarm_r', 'copper', 'copper_r', 'cubehelix', 'cubehelix_r',
          'flag', 'flag_r', 'gist_earth', 'gist_earth_r', 'gist_gray',
          'gist_gray_r', 'gist_heat', 'gist_heat_r', 'gist_ncar',
          'gist_ncar_r', 'gist_rainbow', 'gist_rainbow_r', 'gist_stern',
          'gist_stern_r', 'gist_yarg', 'gist_yarg_r', 'gnuplot',
          'gnuplot2', 'gnuplot2_r', 'gnuplot_r', 'gray', 'gray_r', 'hot',
          'hot_r', 'hsv', 'hsv_r', 'inferno', 'inferno_r', 'jet', 'jet_r',
          'magma', 'magma_r', 'nipy_spectral', 'nipy_spectral_r', 'ocean',
          'ocean_r', 'pink', 'pink_r', 'plasma', 'plasma_r', 'prism',
          'prism_r', 'rainbow', 'rainbow_r', 'seismic', 'seismic_r',
          'spring', 'spring_r', 'summer', 'summer_r', 'tab10', 'tab10_r',
          'tab20', 'tab20_r', 'tab20b', 'tab20b_r', 'tab20c', 'tab20c_r',
          'terrain', 'terrain_r', 'twilight', 'twilight_r',
          'twilight_shifted', 'twilight_shifted_r', 'viridis', 'viridis_r',
          'winter', 'winter_r']
```

Matplotlib has more than 150 available color maps to choose among. The library also offers ways to customize the graphs manually.

14.3 Bar graphs

The `plot` method's `kind` parameter alters the type of chart that Matplotlib renders. A bar graph is an excellent choice to display the counts of unique values in a data set, so let's use it to visualize how many space flights each company sponsored.

First, we'll target the Company Name column and invoke the `value_counts` method to return a Series of mission counts by company:

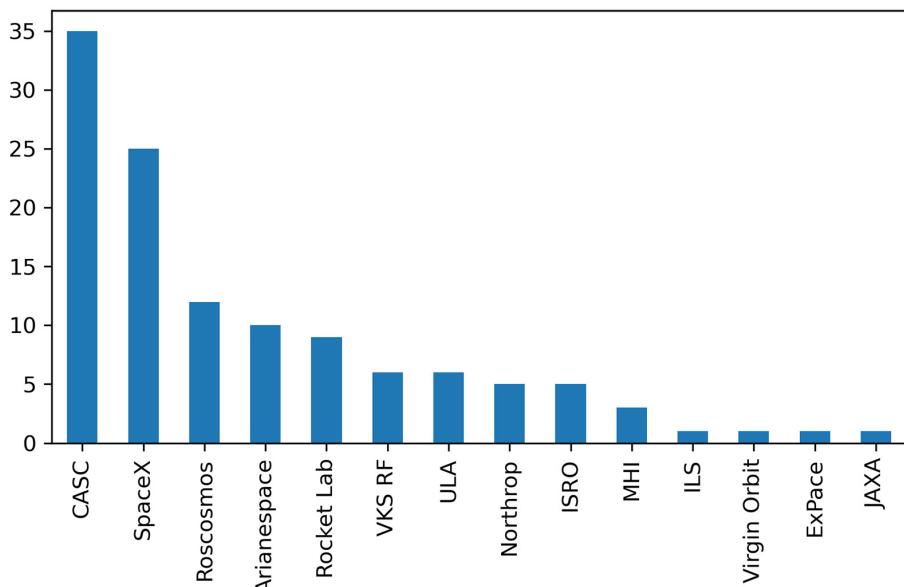
```
In [12] space["Company Name"].value_counts()
```

```
Out [12] CASC           35
          SpaceX         25
          Roscosmos        12
```

```
ArianeSpace    10
Rocket Lab     9
VKS RF        6
ULA            6
Northrop       5
ISRO           5
MHI            3
Virgin Orbit   1
JAXA           1
ILS            1
ExPace          1
Name: Company Name, dtype: int64
```

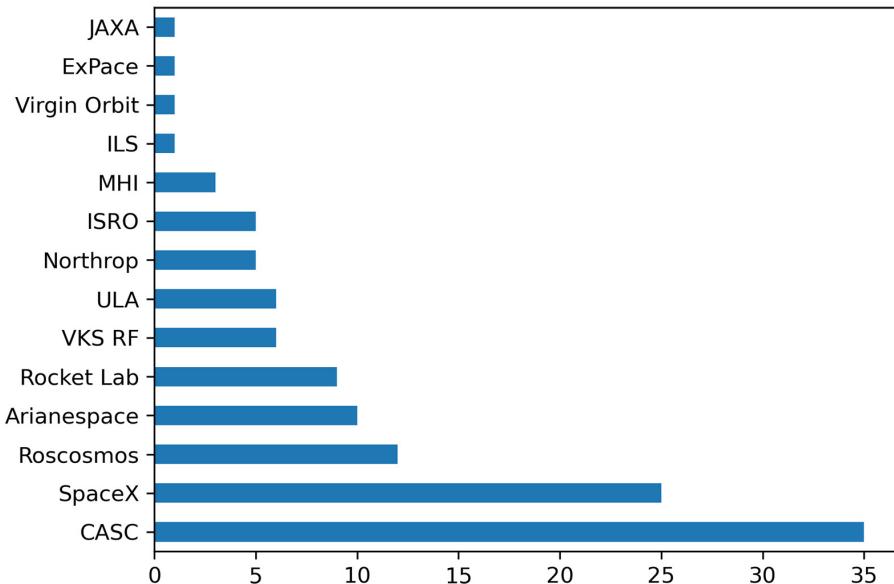
Next, let's invoke the `plot` method on the `Series`, passing an argument of "bar" to the `kind` parameter. Matplotlib once again plots the index labels on the x-axis and the values on the y-axis. It looks as though CASC has the most entries in the data set, followed by SpaceX:

```
In [13] space["Company Name"].value_counts().plot(kind = "bar")
Out [13] <matplotlib.axes._subplots.AxesSubplot at 0x11ecd6310>
```



The graph is a good start, but we have to twist our heads to read the labels. Ouch. Let's change the `kind` argument to "barh" to render a horizontal bar graph instead:

```
In [14] space["Company Name"].value_counts().plot(kind = "barh")
Out [14] <matplotlib.axes._subplots.AxesSubplot at 0x11edf0190>
```



That's a lot better! Now we can easily identify which companies had the greatest number of space flights in the data set.

14.4 Pie charts

A *pie chart* is a visualization in which colored slices add up to form a whole circular pie (much like slices of a pizza). Each piece visually represents the proportion it contributes to the total amount.

Let's use a pie chart to compare the ratio of successful missions to failed missions. The Status column has only two unique values: "Success" and "Failure". First, we'll use the `value_counts` method to count the number of occurrences of each:

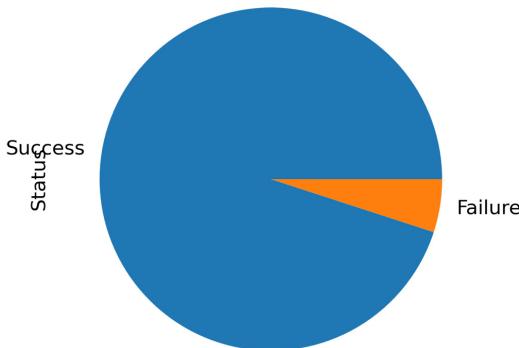
```
In [15] space["Status"].value_counts()

Out [15] Success      114
          Failure       6
          Name: Status, dtype: int64
```

Let's invoke the `plot` method again. This time around, we'll pass the `kind` parameter an argument of "pie":

```
In [16] space["Status"].value_counts().plot(kind = "pie")

Out [16] <matplotlib.axes._subplots.AxesSubplot at 0x11ef9ea90>
```



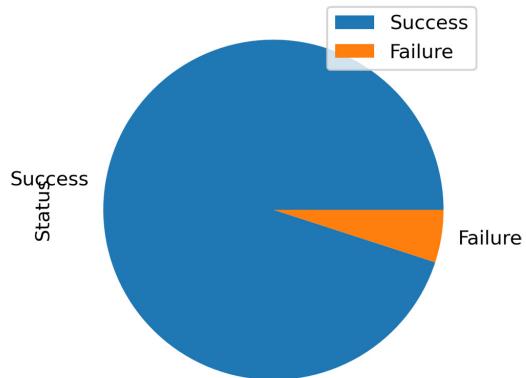
Good news! It looks as though the majority of space flights were successful.

To add a legend to a visualization like this one, we can pass the `legend` parameter an argument of `True`:

```
In [17] space["Status"].value_counts().plot(kind = "pie", legend = True)
```

```
Out [17] <matplotlib.axes._subplots.AxesSubplot at 0x11eac1a10>
```

Matplotlib supports a wide variety of additional charts and graphs, including histograms, scatterplots, and boxplots. We can include additional parameters to customize the aesthetics, labels, legends, and interactivity of these visualizations. We've only scratched the surface of what this powerful library can render.



Summary

- Pandas seamlessly integrates with the Matplotlib library for data visualization. It also plays well with additional plotting libraries within Python's data science ecosystem.
- The `plot` method on a `Series` or `DataFrame` renders a visualization with data from the pandas data structure.
- The default Matplotlib chart is a line graph.
- The `kind` parameter to the `plot` method alters the type of the rendered visualization. Options include line graphs, bar graphs, and pie charts.
- The `colormap` parameter changes the color scheme of the rendered graphic. Matplotlib has dozens of predefined templates, and users can also create their own by adjusting method parameters.

appendix A

Installation and setup

Welcome to the supplementary material! This appendix walks you through installing the Python programming language and the pandas library for the macOS and Windows operating systems. A *library* (also called a *package*) is a toolbox of features that expands a core programming language’s functionalities—an expansion pack or add-on that offers solutions to common challenges that developers face when working with the language. The Python ecosystem includes thousands of packages for domains such as statistics, HTTP requests, and database management.

A *dependency* is a piece of software that we need to install to run another piece of software. Pandas is not a stand-alone package; it has a set of dependencies including the libraries NumPy and pytz. These libraries may require their own dependencies. We don’t have to understand what all these other packages do, but we need to install them for pandas to function.

A.1 *The Anaconda distribution*

Open source libraries are often developed by independent teams of contributors on different timelines. Unfortunately, the isolated development cycles can introduce compatibility issues between library versions. Installing the latest version of a library without upgrading its dependencies may render it dysfunctional, for example.

To simplify the installation and management of pandas and its dependencies, we’ll rely on a Python distribution called Anaconda. A *distribution* is a collection of software that bundles multiple applications and their dependencies in one straightforward installer. With a user base of more than 20 million, Anaconda is the most popular distribution for getting up and running with data science in Python.

Anaconda installs Python and a powerful environment management system called `conda`. An *environment* is an independent sandbox for code execution—a playground of sorts where we can install Python and a selection of packages. To experiment with a different version of Python, a different version of pandas, a different combination of packages, or anything in between, we create a new `conda`

| Environment 1 | Environment 2 | Environment 3 |
|---------------|---------------|---------------|
| Python 2.7 | Python 3.9 | Python 3.8 |
| pandas 0.20.3 | pandas 1.2.0 | django 3.0.7 |
| numpy 1.9.1 | numpy 1.16.6 | flask 1.1.12 |
| | | |
| | | |

Figure A.1 Three Anaconda environments with different Python versions and different packages

environment. Figure A.1 depicts three hypothetical `conda` environments, each with a different version of Python.

The advantage of environments is isolation. Changes in one environment do not affect any other environment, as `conda` stores them in different folders. Thus, we can easily work on multiple projects, each of which requires a different configuration. When you’re installing packages to an environment, `conda` also installs the appropriate dependencies and ensures compatibility between different library versions. In short, `conda` is an effective way to enable multiple installations and configurations of Python tools on your computer.

That’s a big-picture introduction! Now let’s get down to business and install Anaconda. Head to www.anaconda.com/products/individual, and find the section of the page with installer downloads for your operating system. You’ll likely see multiple versions of the Anaconda installer:

- If you’re given a choice between a Graphical Installer and a Command Line Installer, choose the Graphical Installer.
- If you’re given a choice of Python versions, target the most up-to-date one. As with most software, a larger version number denotes a more recent release. Python 3 is newer than Python 2, and Python 3.9 is newer than Python 3.8. When you’re learning a new technology, it’s best to get started with the latest release. Don’t worry; `conda` permits you to create environments with earlier versions of Python if you need them.
- If you’re a Windows user, you may be given a choice between a 64-bit and a 32-bit installer. We’ll discuss which one to select in section A.3.

At this point, the setup process diverges for the macOS and Windows operating systems. Find the appropriate subsection in this appendix, and continue from there.

A.2 *The macOS setup process*

Let’s walk through installing Anaconda on a macOS computer.

A.2.1 *Installing Anaconda in macOS*

Your Anaconda download will consist of a single `.pkg` installer file. The filename will likely include the Anaconda version number and the operating system (such as

Anaconda3-2021.05-MacOSX-x86_64). Locate the installer in your file system, and double-click it to start the installation.

Click the Continue button on the first screen. On the README screen, the installer provides a quick overview of Anaconda that is worth perusing (see figure A.2).

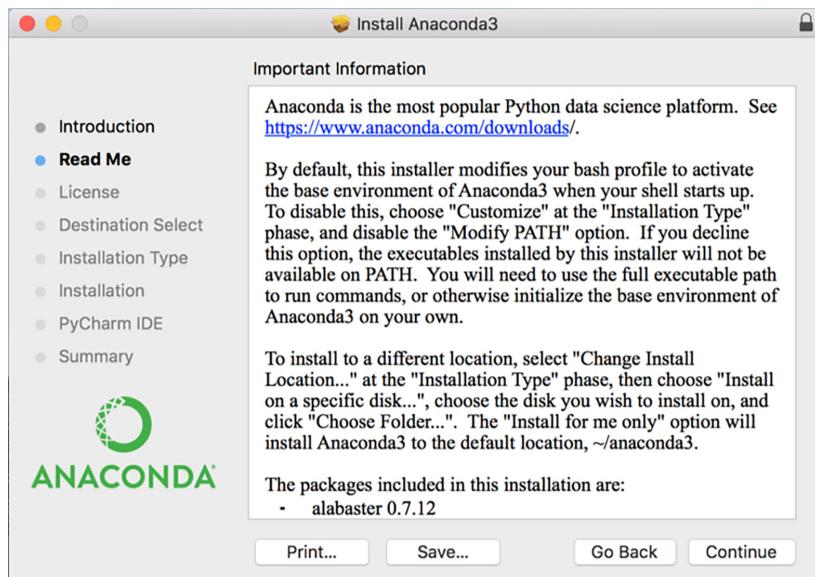


Figure A.2 Anaconda installation screen on a macOS computer

The installation creates a starter conda environment called `base` with a collection of more than 250 preselected data analysis packages. You will be able to create additional environments later. The installer also informs you that it will activate this `base` environment whenever you start your shell; we'll discuss how this process works in section A.2.2. For now, trust that this part of the installation process is required, and proceed onward.

Continue through any remaining screens. Accept the license agreement and the space requirements. You'll be given the option to customize your installation directory; whether you do is entirely up to you. Note that the distribution is self-contained; Anaconda installs itself within one directory on your computer. Thus, if you'd ever like to uninstall Anaconda, you can delete that directory.

Installation may take up to a few minutes. When it completes, click Next until you exit the installer.

A.2.2 Launching Terminal

Anaconda ships with a graphical program called Navigator that makes it easy to create and manage conda environments. Before we launch it, though, we'll use the more traditional Terminal application to issue commands to the conda environment manager.

Terminal is an application for issuing commands to the macOS operating system. Before modern graphical user interfaces (GUIs) existed, users relied exclusively on text-based applications to interact with the computer. In Terminal, you enter text and then press the Enter key to execute it. I'd like us to master Terminal before Anaconda Navigator because it's important to understand the complexity that a piece of software abstracts from us before we rely on its shortcuts.

Open a Finder window, and navigate to the Applications directory, where you'll find the Terminal application within the Utilities folder. Launch the application. I also recommend dragging the Terminal app's icon to the Dock for easy access.

Terminal should list the active conda environment inside a pair of parentheses before its flashing prompt. As a reminder, Anaconda created a base starter environment during installation. Figure A.3 shows a sample Terminal window with the base environment activated.



Figure A.3 Terminal on a macOS machine. The active conda environment is base.

Anaconda will activate the conda environment manager and this base environment whenever we start Terminal.

A.2.3 Common Terminal commands

We need to memorize only a few commands to work effectively with Terminal. In Terminal, we can navigate through our computer's directories the same way that we do in the Finder. The `pwd` (print working directory) command outputs the folder we are in:

```
(base) ~$ pwd  
/Users/boris
```

The `ls` (list) command lists the files and folders inside the current directory:

```
(base) ~$ ls  
Applications Documents Google Drive Movies Pictures anaconda3  
Desktop Downloads Library Music Public
```

Some commands accept flags. A *flag* is a configuration option we add after a command to modify how it executes. Its syntax consists of a sequence of dashes and text characters. Here's one example. The `ls` command by itself shows only public files and

folders. We can add the `--all` flag to the command to display the hidden files as well. Some flags support multiple syntax options. `ls -a`, for example, is a shortcut for `ls --all`. Try both commands for yourself.

The `cd` (change directory) command navigates into a specified directory. Enter the directory name immediately after the command, making sure to include a space. In the next example, we navigate into the `Desktop` directory:

```
(base) ~$ cd Desktop
```

We can output our current location with the `pwd` command:

```
(base) ~/Desktop$ pwd  
/Users/boris/Desktop
```

A pair of dots after `cd` navigates upward in the folder hierarchy:

```
(base) ~/Desktop$ cd ..  
  
(base) ~$ pwd  
/Users/boris
```

Terminal has a powerful autocomplete feature. Inside your user directory, enter `cd Des` and press the Tab key to autocomplete it to `cd Desktop`. Terminal looks at the list of available files and folders, and determines that only `Desktop` matches the `Des` pattern we typed. If there are multiple matches, Terminal will complete a portion of the name. If a directory contains two folders, `Anaconda` and `Analytics`, and you enter the letter `A`, Terminal will autocomplete `Ana`, the common letters in the two options. You'll have to type an additional letter and press the Tab key again for Terminal to autocomplete the remainder of the name.

At this point, we've acquired all the knowledge we need to start working with the `conda` environment manager. Skip to section A.4, where we'll meet up with our Windows friends and set up our first `conda` environment!

A.3 **The Windows setup process**

Let's walk through installing Anaconda on a Windows computer.

A.3.1 **Installing Anaconda in Windows**

The Anaconda installer for Windows is available in both 32-bit and 64-bit versions. These options describe the type of processor installed with your computer. If you are unsure which option to download, open the Start menu, and choose the System Information app. On the app's main screen, you will see a table consisting of Item and Value columns. Look for the `System Type` item; its value will include `x64` if your computer runs a 64-bit version of Windows or `x86` if your computer runs a 32-bit version of Windows. Figure A.4 shows the System Information app on a Windows computer with the `System Type` row highlighted.

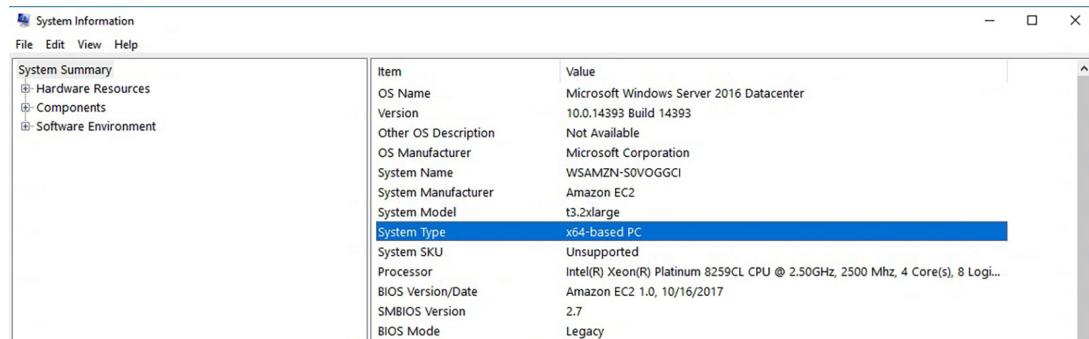


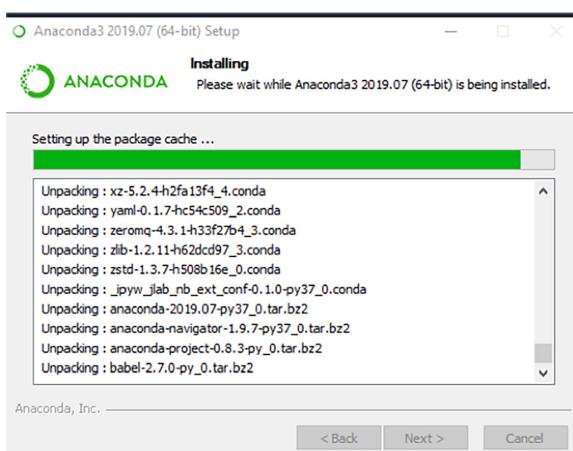
Figure A.4 The System Information app on a 64-bit Windows computer

Your Anaconda download will consist of a single .exe installer file. The filename will include the Anaconda version number and the operating system (such as Anaconda3-2021.05-Windows-x86_64). Locate the file on your file system and double-click it to launch the installer.

Proceed through the first few installation screens. You will be prompted to accept the license agreement, choose whether to install Anaconda for one or all users, and select the installation directory. Selecting the default options is fine.

When you reach the Advanced Installation Options screen, it might be a good idea to deselect the Register Anaconda As My Default Python check box if you already have Python installed on your computer. Deselecting the item prevents the installation from setting Anaconda as the default Python version on your computer. If you're installing Python for the first time, keeping the option selected should be fine.

The installation creates a starter conda environment called `base` with a collection of more than 250 preselected data analysis packages. You will be able to create additional environments later.



Installation can take up to a few minutes. Figure A.5 shows a sample of the installation process. When installation is complete, exit the installer.

Figure A.5 In-progress Anaconda installation on a Windows computer

If you ever want to uninstall Anaconda, launch the Start menu, and choose Add or Remove Programs. Locate the Anaconda program, click the Uninstall button, and follow the steps in the prompt to remove the distribution from your computer. Note that this process will remove all conda environments as well as their installed packages and Python versions.

A.3.2 Launching Anaconda Prompt

Anaconda ships with a graphical program called Navigator that makes it easy to create and manage conda environments. Before we launch it, though, we'll use a more traditional command-line application to issue commands to the conda environment manager. It's important to understand the problems that Navigator solves for us before we rely on its shortcuts.

Anaconda Prompt is an application for issuing text commands to the Windows operating system. We enter a command and then press the Enter key to execute it. Before modern GUIs existed, users relied exclusively on command-based applications like this one to interact with the computer. Open the Start menu, find Anaconda Prompt, and launch the application.

Anaconda Prompt should always list the active conda environment in a pair of parentheses before its flashing prompt. Right now, you should see `base`, the starter environment that Anaconda created during installation. Figure A.6 displays Anaconda Prompt with an active `base` environment.

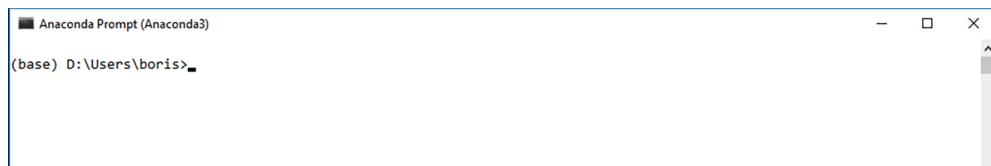


Figure A.6 Anaconda Prompt on a Windows machine. The active conda environment is `base`.

Anaconda Prompt will activate the `base` environment when it launches. In section A.3.4, we'll walk through how to create and activate new environments with `conda`.

A.3.3 Common Anaconda Prompt commands

We need to memorize only a few commands to work effectively with Anaconda Prompt. We can navigate through our computer's directories the same way that we do in Windows Explorer. The `dir` (directory) command lists all files and folders in the current directory:

```
(base) C:\Users\Boris>dir
      Volume in drive C is OS
      Volume Serial Number is 6AAC-5705

      Directory of C:\Users\Boris
```

```
08/15/2019 03:16 PM <DIR> .
08/15/2019 03:16 PM <DIR> ..
09/20/2017 02:45 PM <DIR> Contacts
08/18/2019 11:21 AM <DIR> Desktop
08/13/2019 03:50 PM <DIR> Documents
08/15/2019 02:51 PM <DIR> Downloads
09/20/2017 02:45 PM <DIR> Favorites
05/07/2015 09:56 PM <DIR> Intel
06/25/2018 03:35 PM <DIR> Links
09/20/2017 02:45 PM <DIR> Music
09/20/2017 02:45 PM <DIR> Pictures
09/20/2017 02:45 PM <DIR> Saved Games
09/20/2017 02:45 PM <DIR> Searches
09/20/2017 02:45 PM <DIR> Videos
      1 File(s)  91 bytes
     26 Dir(s) 577,728,139,264 bytes free
```

The `cd` (change directory) command navigates into a specified directory. Enter the directory name immediately after the command, making sure to include a space. In the next example, we navigate into the `Desktop` directory:

```
(base) C:\Users\Boris>cd Desktop
(base) C:\Users\Boris\Desktop>
```

A pair of dots after `cd` navigates upward in the folder hierarchy:

```
(base) C:\Users\Boris\Desktop>cd ..
(base) C:\Users\Boris>
```

Anaconda Prompt has a powerful autocomplete feature. Inside your user directory, enter `cd Des` and press the Tab key to autocomplete it to `cd Desktop`. Anaconda Prompt looks at the list of available files and folders, and determines that only `Desktop` matches the `Des` pattern we typed. If there are multiple matches, Anaconda Prompt will complete a portion of the name. If a directory contains two folders, `Analytics` and `Analytics`, and you enter the letter `A`, Anaconda Prompt will autocomplete `Ana`, the common letters in the two options. You'll have to type an additional letter and press the Tab key again for Prompt to autocomplete the remainder of the name.

At this point, we have all the knowledge we need to start working with the `conda` environment manager. Let's create our first `conda` environment!

A.4 ***Creating a new Anaconda environment***

Congratulations—you've successfully installed the Anaconda distribution on your macOS or Windows machine. Now let's create a sample `conda` environment that we'll use as we work through the book. Please note that the code samples in this section are from a macOS computer. Although outputs may vary slightly between the two operating systems, the Anaconda commands remain the same.

Open Terminal (macOS) or Anaconda Prompt (Windows). Anaconda's default base environment should be active. Look for the presence of parentheses with the word `base` to the left of the prompt.

First, let's confirm that we successfully installed the conda environment manager by issuing a sample command. Here's an easy one: ask conda for its version number. Note that your version may differ from the one in the following output, but as long as the command returns any number at all, conda is successfully installed:

```
(base) ~$ conda --version  
conda 4.10.1
```

The `conda info` command returns a list of technical details about conda. The output includes the currently active environment and its location on your hard drive. Here is an abbreviated version of the output:

```
(base) ~$ conda info  
  
active environment : base  
active env location : /opt/anaconda3  
    shell level : 1  
    user config file : /Users/boris/.condarc  
populated config files : /Users/boris/.condarc  
    conda version : 4.10.1  
    conda-build version : 3.18.9  
    python version : 3.7.4.final.0
```

We can use flags to customize and configure conda commands. A *flag* is a configuration option we add after a command to modify how it executes. Its syntax consists of a sequence of dashes and text characters. The `--envs` flag to the `info` command lists all environments and their locations on the computer. An asterisk (*) marks the active environment:

```
(base) ~$ conda info --envs  
# conda environments:  
#  
base * /Users/boris/anaconda3
```

Every conda command supports the `--help` flag, which outputs documentation for the command. Let's add the flag to the `conda info` command:

```
(base) ~$ conda info --help  
usage: conda info [-h] [--json] [-v] [-q] [-a] [--base] [-e] [-s]  
                  [--unsafe-channels]
```

Display information about current conda install.

Options:

```
optional arguments:  
-h, --help            Show this help message and exit.  
-a, --all             Show all information.  
--base               Display base environment path.  
-e, --envs            List all known conda environments.  
-s, --system          List environment variables.  
--unsafe-channels    Display list of channels with tokens exposed.
```

```
Output, Prompt, and Flow Control Options:
--json           Report all output as json. Suitable for using conda
                  programmatically.
-v, --verbose   Use once for info, twice for debug, three times for
                  trace.
-q, --quiet     Do not display progress bar.
```

Let's create a new playground to play in. The `conda create` command generates a new conda environment. We have to use the `--name` flag to provide a name for the environment. I've chosen a fitting title of `pandas_in_action`; you're welcome to choose whatever environment name you like. When `conda` prompts for confirmation, enter `y` (for yes) and press Enter to confirm:

```
(base) ~$ conda create --name pandas_in_action
Collecting package metadata (current_repodata.json): done
Solving environment: done

## Package Plan ##

environment location: /opt/anaconda3/envs/pandas_in_action

Proceed ([y]/n)? y

Preparing transaction: done
Verifying transaction: done
Executing transaction: done
#
# To activate this environment, use
#
#     $ conda activate pandas_in_action
#
# To deactivate an active environment, use
#
#     $ conda deactivate
```

By default, `conda` installs the latest version of Python in the new environment. To customize the language version, add the keyword `python` at the end of the command, enter an equal sign, and declare the desired version. The next example shows how to create an environment called `sample` with Python 3.7:

```
(base) ~$ conda create --name sample python=3.7
```

Use the `conda env remove` command to delete an environment. Provide the `--name` flag with the environment you'd like to remove. The next code sample deletes the `sample` environment we created:

```
(base) ~$ conda env remove --name sample
```

Now that the `pandas_in_action` environment exists, we can activate it. The `conda activate` command sets the active environment in Terminal or Anaconda Prompt. The text in parentheses before the prompt will change to reflect the new active environment:

```
(base) ~$ conda activate pandas_in_action  
(pandas_in_action) ~$
```

All `conda` commands execute in the context of the active environment. If we ask `conda` to install a Python package, for example, `conda` will now install it within `pandas_in_action`. We want to install the following packages:

- The core `pandas` library
- The `jupyter` development environment where we'll be writing our code
- The `bottleneck` and `numexpr` libraries for speed accelerations

The `conda install` command downloads and install packages in the active `conda` environment. Add the four packages immediately after the command, separated by spaces:

```
(pandas_in_action) ~$ conda install pandas jupyter bottleneck numexpr
```

As mentioned earlier, these four libraries have dependencies. The `conda` environment manager will output a list of all packages that it needs to install. Following is a shortened version of the output. It's OK if you see a different list of libraries or version numbers; `conda` takes care of compatibility.

```
Collecting package metadata (repodata.json): done
Solving environment: done

## Package Plan ##

environment location: /opt/anaconda3/envs/pandas_in_action

added / updated specs:
- bottleneck
- jupyter
- numexpr
- pandas
```

The following packages will be downloaded:

| package | build | |
|----------------------|-------------------|--------|
| appnope-0.1.2 | py38hecd8cb5_1001 | 10 KB |
| argon2-cffi-20.1.0 | py38haf1e3a3_1 | 44 KB |
| async_generator-1.10 | py_0 | 24 KB |
| certifi-2020.12.5 | py38hecd8cb5_0 | 141 KB |
| cffi-1.14.4 | py38h2125817_0 | 217 KB |
| ipython-7.19.0 | py38h01d92e1_0 | 982 KB |
| jedi-0.18.0 | py38hecd8cb5_0 | 906 KB |
| #... more libraries | | |

Type `y` for yes and press Enter to install all packages and their dependencies.

If you ever forget the packages installed in an environment, use the `conda list` command to see a complete list. The output includes each library's version:

```
(pandas_in_action) ~$ conda list

# packages in environment at /Users/boris/anaconda3/envs/pandas_in_action:
#
# Name            Version      Build  Channel
jupyter          1.0.0       py39hecd8cb5_7
pandas           1.2.4       py39h23ab428_0
```

If you ever want to remove a package from an environment, use the `conda uninstall` command. Here's what that command would look like with pandas:

```
(pandas_in_action) ~$ conda uninstall pandas
```

We're ready to explore our development environment. We can launch the Jupyter Notebook application with the command `jupyter notebook`:

```
(pandas_in_action) ~$ jupyter notebook
```

Jupyter Notebook starts a local server on your computer to run the core Jupyter application. We need a server running continually so that it can observe the Python code we write and execute it immediately.

The Jupyter Notebook application should open in your system's default web browser. You can also access the application by navigating to `localhost:8888/` in the address bar; localhost refers to your computer, and 8888 is the port on which the app is running. Much as a dock includes multiple ports to welcome multiple ships, your computer (localhost) has multiple ports to allow multiple programs to run on your computer's local server. Figure A.7 shows the main interface of the Jupyter Notebook interface, listing the files and folders in the current directory.

The Jupyter Notebook interface is similar to the Finder (macOS) or Windows Explorer (Windows). Folders and files are organized in alphabetical order. You can click through folders to navigate into the next directory and use the breadcrumbs on



Figure A.7 Jupyter Notebook's main interface

top to navigate upward. Poke around for a few seconds. When you get the hang of navigation, close the browser.

Note that closing the browser does not shut down the running Jupyter server. We need to press the keyboard shortcut Ctrl-C twice in Terminal or Anaconda Prompt to terminate the Jupyter server.

Note that every time you launch Terminal (macOS) or Anaconda Prompt (Windows), you'll have to activate the `pandas_in_action` environment again. Although Anaconda's base environment includes pandas, I recommend creating a new environment for every Python book or tutorial you work through. Multiple environments ensure separation between Python dependencies across different projects. One tutorial may use pandas 1.1.3, for example, and another may use pandas 1.2.0. There are fewer chances for technical errors when you install, upgrade, and work with dependencies in isolation.

Here's a reminder of what to do each time you launch Terminal or Anaconda Prompt:

```
(base) ~$ conda activate pandas_in_action
(pandas_in_action) ~$ jupyter notebook
```

The first command activates the `conda` environment, and the second command launches Jupyter Notebook.

A.5 Anaconda Navigator

Anaconda Navigator is a graphical program for managing `conda` environments. Although its feature set is not as comprehensive as that of the `conda` command-line tool, Anaconda Navigator offers a visual, beginner-friendly way to create and manage environments with `conda`. You can find Anaconda Navigator inside the Applications folder in the Finder (macOS) or on the Start menu (Windows). Figure A.8 shows the home screen of the Anaconda Navigator app.

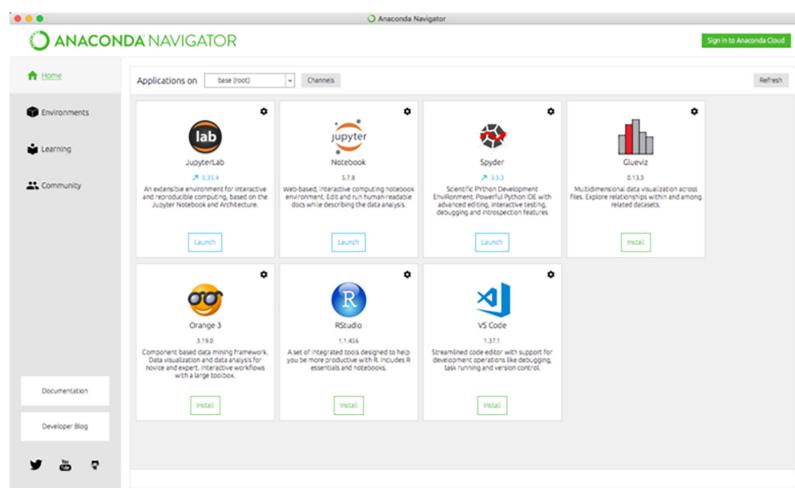


Figure A.8
Anaconda
Navigator
home screen

Click the Environments tab on the left menu to display a list of all environments. Select a conda environment to see its installed packages, including their descriptions and version numbers.

On the bottom pane, click the Create button to launch a new environment-creation prompt. Give the environment a name, and select a version of Python to install. The resulting dialog box displays the location where conda will create the environment (figure A.9).

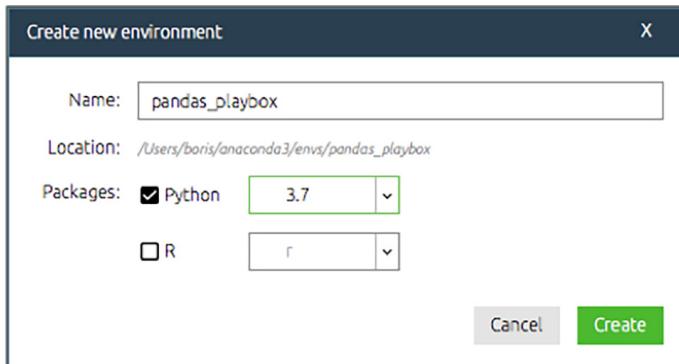


Figure A.9 Creating a new Anaconda environment

To install a package, select an environment in the left list. Above the list of packages, click the drop-down menu and choose All to see all packages (figure A.10).

In the search box on the right, search for a sample library, such as pandas. Locate it in the search results, and select the corresponding check box (figure A.11).

Finally, click the green Apply button in the bottom-right corner to install the library.



Figure A.10
Anaconda package search

| Search Environments | Channels | Update index... | pandas | |
|---------------------|----------|-----------------|-------------------|---------|
| All | | | | |
| Name | | | | Version |
| base (root) | | | geopandas | 0.8.1 |
| pandas_in_action | | | pandas | 1.2.4 |
| pandas_playbox | ▶ | | pandas-datareader | 0.9.0 |
| | | | pandas-profiling | 2.9.0 |
| | | | pandasql | 0.7.3 |

Figure A.11 Searching for and selecting the pandas package in Anaconda Navigator

Let's delete the `pandas_playbox` environment we created. We don't need it because we already created a `pandas_in_action` environment in Terminal or Anaconda Prompt. Make sure to select `pandas_playbox` in the left-side environment list. Then click the Remove button on the bottom panel and again in the confirmation dialog box (figure A.12).

To launch Jupyter Notebook from Anaconda Navigator, click the Home tab of the left navigation menu. On this screen, you'll see tiles for the applications installed in the current environment. The top of the screen has a drop-down menu from which you can choose the active conda environment. Make sure to select the `pandas_in_action` environment we created for this book. Then you can launch Jupyter Notebook by clicking its application tile. This action is equivalent to executing `jupyter notebook` from Terminal or Anaconda Prompt.

A.6 The basics of Jupyter Notebook

Jupyter Notebook is an interactive development environment for Python, consisting of one or more cells, each of which holds Python code or Markdown. *Markdown* is a text formatting standard that we can use to add headers, text paragraphs, bulleted lists, embedded images, and more to the Notebook. We use Python to write our logic and Markdown to organize our thoughts. As you proceed through the book, feel free to use Markdown to take notes on the material. The complete documentation for Markdown is available at <https://daringfireball.net/projects/markdown/syntax>.

On the Jupyter launch screen, click the New button on the right menu, and choose Python 3 to create a new Notebook (figure A.13).

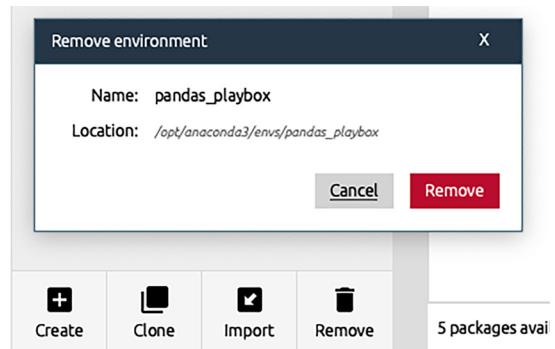


Figure A.12 Deleting the environment we created in Anaconda Navigator

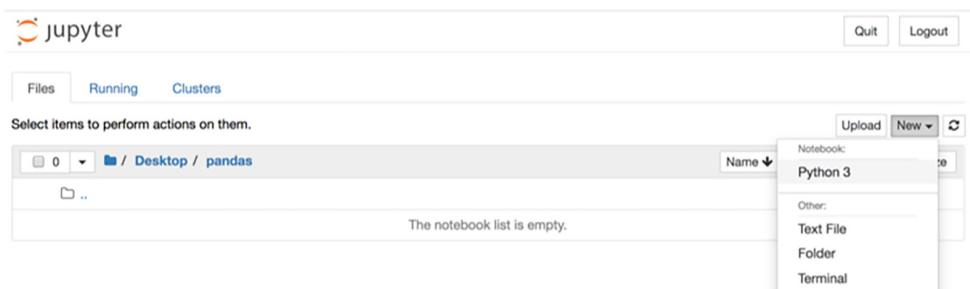


Figure A.13 Creating a Jupyter Notebook

To give the Notebook a name, click the Untitled text at the top and enter a name in the dialog box. Jupyter Notebook saves its files with the .ipynb extension, short for IPython Notebooks, the predecessor of Jupyter Notebooks. You can navigate back to your Jupyter Notebook tab to see the new .ipynb file in the directory.

A Notebook operates in two modes: Command and Edit. Clicking a cell or pressing Enter while the cell is focused triggers Edit mode. Jupyter highlights the cell with a green border. In Edit mode, Jupyter interprets your keyboard presses literally. We use this mode to type characters in a selected cell. Figure A.14 displays a sample Jupyter cell in Edit mode.

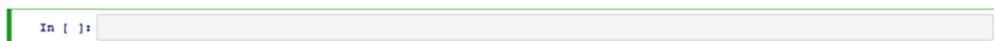


Figure A.14 Empty Jupyter Notebook cell in Edit mode

Below the Notebook’s navigation menu, you’ll find a toolbar for common shortcuts. A drop-down menu at the right end of the toolbar displays the focused cell’s type. Click the drop-down menu to reveal a list of available cell options, and choose Code or Markdown to change a cell to that type (figure A.15).

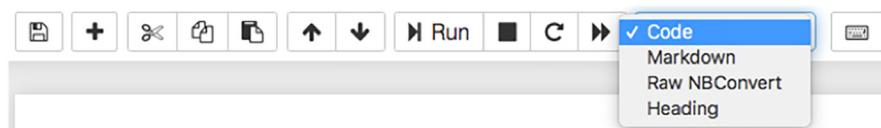


Figure A.15 Changing the type of a Jupyter Notebook cell

One of the best features of Jupyter Notebooks is its trial-and-error approach to development. We enter Python code in a Code cell and then execute it. Jupyter outputs the result below the cell. We check whether the result matches what we expect and continue the process. This approach encourages active experimentation; we’re always a keyboard press away from seeing the difference that a line of code makes.

Let’s execute some basic Python code. Enter the following mathematical expression inside the Notebook’s first cell and then click the Run button on the toolbar to execute it:

```
In [1]: 1 + 1  
Out [1]: 2
```

The box to the left of the code (displaying the number 1 in the preceding example) marks the cell’s execution order relative to the launch or restart of the Jupyter Notebook. You can execute the cells in any order, and you can execute the same cell multiple times.

As you read through the book, I encourage you to experiment by executing different snippets of code in your Jupyter cells. Thus, it is OK if your execution numbers do not match those in the text.

If a cell contains multiple lines of code, Jupyter will output the evaluation of the last expression. Note that Python still runs all the code in the cell; we see only the last expression.

```
In [2]: 1 + 1
        3 + 2
```

```
Out [2]: 5
```

The *interpreter* is the software that parses your Python source code and executes it. Jupyter Notebook relies on IPython (Interactive Python), an enhanced interpreter with extra features for developer productivity. As one example, you can use the Tab key to reveal available methods and attributes on any Python object. The next example shows the available methods on a Python string. Type any string and a dot; then press Tab to see the dialog box. Figure A.16 shows an example with a string. If you're unfamiliar with Python's core data structures, see appendix B for a comprehensive introduction to the language.

You can enter any amount of Python in a Code cell, but it's best to keep a cell's size reasonably small to improve readability and comprehension. If your logic is complex, split the operations across several cells.

You can use either of two keyboard shortcuts to execute a cell in Jupyter Notebook. Press Shift-Enter to execute a cell and move focus to the next cell, and press Ctrl-Enter to execute a cell and maintain focus on the original cell. Practice reexecuting the first two cells to see this difference in action.

Press the Esc key to activate Command mode, a management mode for the Notebook. The available operations in this mode are more global; they affect the Notebook as a whole rather than one specific cell. In this mode, keyboard characters serve as shortcuts. Here are some helpful keyboard shortcuts to use when the Notebook is in Command mode:

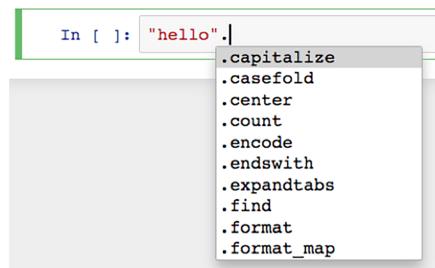


Figure A.16 Jupyter Notebook's autocomplete features

| Keyboard shortcut | Description |
|-------------------------|--|
| Up- and down-arrow keys | Navigate through Notebook cells. |
| a | Create a new cell above the selected cell. |
| b | Create a new cell below the selected cell. |

| Keyboard shortcut | Description |
|--|--|
| c | Copy the contents of a cell. |
| x | Cut the contents of a cell. |
| v | Paste a copied or cut cell into the cell below the selected one. |
| d+d | Delete a cell. |
| z | Reverse a deletion. |
| y | Change the cell type to Code. |
| m | Change the cell type to Markdown. |
| h | Show the help menu, which has a complete list of keyboard shortcuts. |
| Command-S (macOS) or Ctrl-S (Windows) | Save the Notebook. Note that Jupyter Notebook also has autosave functionality. |

To clear everything from the Notebook’s memory, choose Kernel from the top-level menu and then choose Restart. Additional options are available to clear cell outputs and rerun all cells in the Notebook.

Let’s say that we’ve had enough fun with our Notebook for the day and decide it’s time to exit. A Notebook continues running in the background even when we close its browser tab. To close it, navigate to the Running tab on the top menu of the Jupyter launch screen, and click the Shutdown button next to the Notebook (figure A.17).



Figure A.17 Shutting down a Jupyter Notebook

After we shut down all Notebooks, we have to terminate the Jupyter Notebook application. Close the browser tab with the Jupyter application. In Terminal or Anaconda Prompt, press Ctrl+C twice to terminate the local Jupyter server.

At this point, you’re all set to start writing Python and pandas code in Jupyter. Good luck!

appendix B

Python crash course

The pandas library is built on top of Python, a popular programming language first released in 1991 by Dutch developer Guido van Rossum. A *library* (also called a *package*) is a toolbox of features that expands the core functionalities of a programming language. Libraries accelerate developer productivity by providing solutions to everyday problems such as database connections, code quality, and testing. Most Python projects use libraries. After all, why solve a problem from scratch if somebody has already solved it? More than 300,000 libraries are available to download from the Python Package Index (PyPi), a centralized online repository of Python packages. Pandas is one of those 300,000 libraries; it implements complex data structures that excel at storing and manipulating multidimensional data. Before we explore what pandas adds to Python, it's important to see what's available in the base language.

Python is an object-oriented programming (OOP) language. The OOP paradigm views a software program as being a collection of objects that talk to one another. An *object* is a digital data structure that stores information and provides ways for it to be accessed and manipulated. Each object has a responsibility or purpose for existing. We can think of each object as being an actor in a play and the software program as being a performance.

A helpful way to think of objects is as digital building blocks. Consider a spreadsheet software like Excel. As users, we can discern the differences among a workbook, a worksheet, and a cell. A workbook holds worksheets, a worksheet holds cells, and cells hold values. We view these three entities as three distinct containers of business logic, each with a designated responsibility, and we interact with them in different ways. When building object-oriented computer programs, developers think in the same manner, identifying and building the “blocks” that need to exist for a program to run.

You'll often hear the expression “Everything is an object” in the Python community. The statement means that the language implements all its data types, even

simple ones such as numbers and text, as objects. Libraries like pandas add a new collection of objects—an additional set of building blocks—to the language.

As a data analyst turned software engineer, I've witnessed the Python proficiency requirements for many roles in the industry. I can state from experience that you do not need to be an advanced programmer to be productive with pandas. Basic understanding of Python's core mechanics, however, will significantly accelerate the speed at which you can pick up the library. This appendix highlights the key language essentials you need to know to be successful.

B.1 Simple data types

Data comes in a variety of types. A whole number like 5 is of a different type than a decimal number like 8.46. Both 5 and 8.46 are different from a text value like "Bob".

Let's begin with an exploration of the core data types built into Python. Make sure that you've installed the Anaconda distribution and set up a `conda` environment that includes the Jupyter Notebook coding environment. If you need help, see the installation instructions in appendix A. Activate the `conda` environment you created for this book, execute the command `jupyter notebook`, and create a new Notebook.

A quick note before we start: in Python, the hashtag symbol (#) creates a comment. A *comment* is a line of text that Python ignores when it processes the code. Developers use comments to provide inline documentation for their code. Here's an example:

```
# Adds two numbers together  
1 + 1
```

We can also add a comment after a piece of code. Python ignores everything after the hashtag symbol. The rest of the line executes normally:

```
1 + 1 # Adds two numbers together
```

Although the previous example evaluates to 2, the next example produces no output. The comment effectively disables the line, so Python ignores the addition:

```
# 1 + 1
```

I've used comments in code cells throughout the book to provide supplemental commentary on the operations at hand. You do not need to copy the comments into your Jupyter Notebook.

B.1.1 Numbers

An *integer* is a whole number; it has no fractional or decimal component. An example is 20:

```
In [1] 20  
Out [1] 20
```

An integer can be any positive number, negative number, or zero. Negative numbers are prefixed by a minus sign (-):

```
In [2] -13  
Out [2] -13
```

A *floating-point number* (colloquially called a *float*) is a number with a fractional or decimal component. We use a dot to declare a decimal point. 7.349 is an example of a float:

```
In [3] 7.349  
Out [3] 7.349
```

Integers and floating-point numbers represent different data types in Python or, equivalently, different objects. Look for the presence of a decimal point to distinguish between the two. The value 5.0 is a floating-point object, for example, whereas 5 is an integer object.

B.1.2 Strings

A *string* is a collection of zero or more text characters. We declare a string by wrapping a piece of text in a pair of single, double, or triple quotes. There are differences among the three options, but they are insignificant for beginners. We'll be sticking with double quotes throughout the book. Jupyter Notebook's output for the three syntax options is identical:

```
In [4] 'Good morning'  
Out [4] 'Good morning'  
In [5] "Good afternoon"  
Out [5] 'Good afternoon'  
In [6] """Good night"""  
Out [6] 'Good night'
```

Strings are not limited to alphabetic characters; they can include digits, spaces, and symbols. Consider the next example, which includes seven alphabetic characters, a dollar sign, two digits, a space, and an exclamation point:

```
In [7] "$15 dollars!"  
Out [7] '$15 dollars!'
```

Use the presence of quotes to identify a string visually. Many beginners are confused by a value like "5", which is a string that holds a single numeric character. "5" is not an integer.

An *empty string* has no characters. We create it with a pair of quotes with nothing between them:

```
In [8] ""  
Out [8] ''
```

The length of a string refers to the count of its characters. The string "Monkey business", for example, has a length of 15 characters; there are six characters in Monkey, eight characters in business, and one space between the two words.

Python assigns a number to every string character based on its order in line. The number is called the *index*, and it starts counting from 0. In the string "car",

- "c" is at index position 0.
- "a" is at index position 1.
- "r" is at index position 2.

A string's final index position is always one less than its length. The string "car" has a length of 3, so its final index position is 2. Zero-based indexes tend to confuse new developers; it's a difficult mental shift to make because we have been taught since grade school to start counting from 1.

We can extract any character from a string by its index position. After the string, enter a pair of square brackets with the index value. The next example pulls out the "h" character in "Python". The "h" character is the fourth character in sequence, so it has an index of 3:

```
In [9] "Python"[3]
Out [9] 'h'
```

To pull from the end of the string, provide a negative value within the square brackets. A value of -1 extracts the last character, -2 extracts the second-to-last character, and so on. The next example targets the fourth-to-last character in Python, the "t":

```
In [10] "Python"[-4]
Out [10] 't'
```

In the preceding example, "Python"[2] would yield the same "t" output.

We can use a special syntax to extract multiple characters from a string. The process is called *slicing*. Place two numbers inside the square brackets, separated by a colon. The left-side value sets the starting index. The right-side value sets the final index. The starting index is inclusive; Python includes the character at that index. The ending index is exclusive; Python excludes the character at that index. Tricky, I know.

The next example pulls all characters from index position 2 (inclusive) up to index position 5 (exclusive). The slice includes the characters "t" at index 2, "h" at index 3, and "o" at index 4:

```
In [11] "Python"[2:5]
Out [11] 'tho'
```

If 0 is the starting index, we can remove it from the square brackets and get the same result. Choose whatever syntax option fits you better:

```
In [12] # The two lines below are equivalent
"Python"[0:4]
"Python"[:4]
Out [12] 'Pyth'
```

Here's another shortcut: to extract characters from an index to the string's end, remove the ending index. The following example shows two options for pulling out the characters from "h" (index 3) to the end of the "Python" string:

```
In [13] # The two lines below are equivalent
      "Python"[3:6]
      "Python"[3:]
```



```
Out [13] 'hon'
```

We can also remove both numbers. A single colon tells Python "Go from the beginning to the end." The result is a copy of the string:

```
In [14] "Python"[:]
```



```
Out [14] 'Python'
```

We can mix and match positive and negative index positions in a string slice. Let's pull from index 1 ("y") up to the last character in the string ("n"):

```
In [15] "Python"[1:-1]
```



```
Out [15] 'ytho'
```

We can also pass an optional third number to set the *step interval*—the gap to jump between every two index positions. The next example pulls out the characters from index positions 0 (inclusive) up to 6 (exclusive) in intervals of 2. This slice includes the characters "P", "t", and "o", which are at index positions 0, 2, and 4:

```
In [16] "Python"[0:6:2]
```



```
Out [16] 'Pto'
```

Here's a cool trick: we can pass in -1 as the third number to proceed backward from the end of the list to the beginning. The result is a reversed string:

```
In [17] "Python"[::-1]
```



```
Out [17] 'nohtyP'
```

Slicing comes in handy for extracting snippets of text from larger strings—a topic we cover extensively in chapter 6.

B.1.3 Booleans

The *Boolean* data type represents the logical idea of truth. It can be only one of two values: `True` or `False`. The Boolean is named after English mathematician and philosopher George Boole. It usually models an either-or relationship: yes or no, on or off, valid or invalid, active or inactive, and so on.

```
In [18] True
```



```
Out [18] True
```



```
In [19] False
```



```
Out [19] False
```

We often arrive at a Boolean data type through a calculation or comparison, which we'll see in section B.2.2.

B.1.4 **The None object**

The `None` object represents nothingness or the absence of a value. Like a Boolean, it's a tricky type to wrap our heads around because it's more abstract than a concrete value such as an integer.

Suppose that we decide to measure our town's daily temperature for a week but forget to take a reading on Friday. The temperatures for six of the seven days would be integers. How could we log the temperature for the missing day? We might enter something like "missing" or "unknown" or "null". The `None` object models the same idea in Python. The language needs something to communicate the absence of a value. It requires an object that stands in and announces that a value is missing, does not exist, or is not needed. Jupyter Notebook outputs nothing when we execute a cell with `None`:

```
In [20] None
```

As with a Boolean, we'll usually arrive at a `None` value rather than create it manually. We'll explore the object in greater detail as we work through the book.

B.2 **Operators**

An *operator* is a symbol that performs an operation. One classic example from elementary school is the addition operator: the plus sign (`+`). The values that an operator works on are called *operands*. In the expression `3 + 5`,

- `+` is the operator.
- 3 and 5 are the operands.

In this section, we'll explore the various mathematical and logical operators built into Python.

B.2.1 **Mathematical operators**

Let's write out the mathematical expression from the introduction. Jupyter will output the calculation directly below the cell:

```
In [21] 3 + 5
```

```
Out [21] 8
```

It is conventional to add a space on both sides of an operator to make the code easier to read. The next two examples illustrate subtraction (`-`) and multiplication (`*`):

```
In [22] 3 - 5
```

```
Out [22] -2
```

```
In [23] 3 * 5
```

```
Out [23] 15
```

`**` is the exponentiation operator. The next example raises 3 to the power of 5 (3 multiplied by itself 5 times):

```
In [24] 3 ** 5
Out [24] 243
```

The `/` symbol performs division. The next example divides 3 by 5:

```
In [25] 3 / 5
Out [25] 0.6
```

In mathematical terminology, the *quotient* is the result of dividing one number by another. Division with the `/` operator always returns a floating-point quotient, even if the divisor fits evenly into the dividend:

```
In [26] 18 / 6
Out [26] 3.0
```

Floor division is an alternative type of division that removes the decimal remainder from a quotient. It requires two forward slashes (`//`) and returns an integer quotient. The next example demonstrates the differences between the two operators:

```
In [27] 8 / 3
Out [27] 2.6666666666666665
In [28] 8 // 3
Out [28] 2
```

The *modulo* operator (`%`) returns the remainder of a division. 2 is the remainder when 5 is divided by 3:

```
In [29] 5 % 3
Out [29] 2
```

We can also use the addition and multiplication operators with strings. The plus sign joins two strings. The technical word for this process is *concatenation*.

```
In [30] "race" + "car"
Out [30] 'racecar'
```

The multiplication sign repeats a string a given number of times:

```
In [31] "Mahi" * 2
Out [31] 'MahiMahi'
```

An object's type determines the operations and operators that it supports. We can divide integers, for example, but we cannot divide strings. The primary skill in OOP is identifying the object you're working with and the actions it can perform.

We can concatenate a string to another string, and we can add a number to another number. But what happens when we try to add a string and a number?

```
In [32] 3 + "5"
-----
TypeError                                     Traceback (most recent call last)
<ipython-input-9-d4e36ca990f8> in <module>
----> 1 3 + "5"

TypeError: unsupported operand type(s) for +: 'int' and 'str'
```

Uh-oh. This example is our first exposure to a Python error—one of several dozen built into the language. The technical name for an error is an *exception*. Like everything else in Python, an exception is an object. Whenever we make a syntactical or logical mistake, Jupyter Notebook displays an analysis that includes the name of the error and the line number that triggered it. The technical term *raise* is often used to indicate that Python encountered an exception. We could say, “I tried to add a number and a string, and Python raised an exception.”

Python raises a `TypeError` exception when we use a wrong data type in an operation. In the preceding example, Python observed a number and a plus sign, and assumed that another number would follow. Instead, it received a string, which it cannot add to an integer. We’ll see how we can convert an integer to a string (and vice versa) in section B.4.1.

B.2.2 Equality and inequality operators

Python considers two objects to be equal if they hold the same value. We can compare the equality of two objects by placing them on opposite sides of the equality operator (`==`). The operator returns `True` if the two objects are equal. As a reminder, `True` is a Boolean value.

```
In [33] 10 == 10
Out [33] True
```

Be careful: the equality operator has two equal signs. Python reserves a single equal sign for a completely different operation that we’ll cover in section B.3.

The equality operator returns `False` if the two objects are unequal. `True` and `False` are the only valid values for Booleans:

```
In [34] 10 == 20
Out [34] False
```

Here are some examples of the equality operator with strings:

```
In [35] "Hello" == "Hello"
Out [35] True
In [36] "Hello" == "Goodbye"
Out [36] False
```

Case sensitivity matters when comparing two strings. In the next example, one string starts with a capital "H", and the other starts with a lowercase "h", so Python considers the two strings to be unequal:

```
In [37] "Hello" == "hello"  
Out [37] False
```

The inequality operator (`!=`) is the inverse of the equality operator; it returns `True` if two objects are unequal. It is `True`, for example, that 10 is not equal to 20:

```
In [38] 10 != 20  
Out [38] True
```

Similarly, the string "Hello" is not equal to the string "Goodbye":

```
In [39] "Hello" != "Goodbye"  
Out [39] True
```

The inequality operator returns `False` if the two objects are equal:

```
In [40] 10 != 10  
Out [40] False  
  
In [41] "Hello" != "Hello"  
Out [41] False
```

Python supports mathematical comparisons between numbers. The `<` operator checks whether the operand on the left side is smaller than the operand on the right side. The next example checks whether -5 is less than 3:

```
In [42] -5 < 3  
Out [42] True
```

The `>` operator checks whether the operand on the left side is greater than the operand on the right side. The next example evaluates whether 5 is greater than 7; the result is `False`.

```
In [43] 5 > 7  
Out [43] False
```

The `<=` operand checks whether the left-side operand is less than or equal to the right-side operand. Here, we check whether 11 is less than or equal to 11:

```
In [44] 11 <= 11  
Out [44] True
```

The complementary `>=` operand checks whether the left-side operand is greater than or equal to the right-side operand. The next example checks whether 4 is greater than or equal to 5:

```
In [45] 4 >= 5
Out [45] False
```

Pandas enables us to apply comparisons like these to whole columns of data, a topic we cover in chapter 5.

B.3 Variables

A *variable* is a name we assign to an object; we can compare it with the address of a house, because it is a label, a reference, and an identifier. Variable names should be clear and descriptive, describing the data that the object is storing and the purpose it serves in our application. `revenues_for_quarter4` is a better variable name than `r` or `r4`, for example.

We assign a variable to an object with the assignment operator, a single equal sign (`=`). The next example assigns four variables (`name`, `age`, `high_school_gpa`, and `is_handsome`) to four different data types (string, integer, floating-point, and Boolean):

```
In [46] name = "Boris"
        age = 28
        high_school_gpa = 3.7
        is_handsome = True
```

The execution of a cell with a variable assignment does not yield any output in Jupyter Notebook, but afterward we are able to use the variable in any cell in the Notebook. The variable is a substitute for the value it holds:

```
In [47] name
Out [47] 'Boris'
```

A variable name must start with a letter or an underscore. After the first letter, it can hold only letters, numbers, or underscores.

As their name suggests, variables can hold values that vary over a program's execution. Let's reassigned the `age` variable to a new value of 35. After we execute the cell, the `age` variable's reference to its former value, 28, will be lost:

```
In [48] age = 35
        age
Out [48] 35
```

We can use the same variable on both sides of the assignment operator. Python always evaluates the right side of the equal sign first. In the next example, Python adds the value of `age` at the start of the cell's execution, 35, to 10. The resulting sum, 45, is saved to the `age` variable:

```
In [49] age = age + 10
        age
Out [49] 45
```

Python is a *dynamically typed* language, which means that variables do not know anything about data types. A variable is a placeholder name for any object in the program. Only the object knows its data type. Therefore, we can reassign variables from an object of one type to another. The next example reassigns the `high_school_gpa` variable from its original floating-point value of 3.7 to a string of "A+":

```
In [50] high_school_gpa = "A+"
```

Python raises a `NameError` exception when a variable does not exist in the program:

```
In [51] last_name
```

```
-----  
NameError                                 Traceback (most recent call last)  
<ipython-input-5-e1aeda7b4fde> in <module>  
----> 1 last_name  
  
NameError: name 'last_name' is not defined
```

You'll typically encounter a `NameError` exception when you mistype a variable name. This exception is nothing to fear; correct the spelling, and execute the cell again.

B.4 Functions

A *function* is a procedure consisting of one or more steps. Think of a function as being a cooking recipe in a programming language—a series of instructions that yields a consistent result. Functions enable reusability in software. Because a function captures a piece of business logic from start to finish, we can reuse it when we have to perform the same operation multiple times.

We declare a function and then execute it. In the declaration, we write the steps that the function should take. In the execution, we run the function. Sticking to our cooking analogy, declaring a function is equivalent to writing down a recipe, and executing a function is equivalent to cooking the recipe. The technical term for executing a function is *calling* it or *invoking* it.

B.4.1 Arguments and return values

Python ships with more than 65 built-in functions. We can also declare our own custom functions. Let's dive into an example. The built-in `len` function returns the length of a given object. The concept of length varies from data type to data type; for a string, it's a count of its characters.

We invoke a function by entering its name and a pair of opening and closing parentheses. Much as a cooking recipe can accept ingredients, a function invocation can accept inputs called *arguments*. We pass arguments sequentially inside the parentheses, separated by commas.

The `len` function expects one argument: the object whose length it should calculate. The next example passes a string argument of "Python is fun" to the function:

```
In [52] len("Python is fun")
```

```
Out [52] 13
```

A cooking recipe produces a final output of a meal. Similarly, a Python function produces a final output called a *return value*. In the preceding example, `len` was the invoked function, "Python is fun" was its single argument, and 13 was the return value.

That's all there is to it! A function is a procedure that is invoked with zero or more arguments and produces a return value.

Here are three more popular built-in functions in Python:

- `int`, which converts its argument to an integer
- `float`, which converts its argument to a floating-point number
- `str`, which converts its argument to a string

The next three examples showcase these functions in action. The first example invokes the `int` function with a string argument of "20" and produces a return value of 20. Can you identify the arguments and return values for the remaining two functions?

```
In [53] int("20")
Out [53] 20
In [54] float("14.3")
Out [54] 14.3
In [55] str(5)
Out [55] '5'
```

Here's another common error: Python raises a `ValueError` exception when a function receives an argument with the right data type but an inappropriate value. In the next example, the `int` function receives a string (an appropriate type), but the string is one from which it is impossible to extract an integer:

```
In [56] int("xyz")
-----
ValueError                                                 Traceback (most recent call last)
<ipython-input-6-ed77017b9e49> in <module>
----> 1 int("xyz")
ValueError: invalid literal for int() with base 10: 'xyz'
```

Another popular built-in function is `print`, which outputs text to the screen. It accepts any number of arguments. The function often proves to be helpful when we want to observe a variable's value throughout a program's execution. The next example invokes the `print` function four times with the `value` variable, whose value changes several times:

```
In [57] value = 10
        print(value)

        value = value - 3
        print(value)
```

```
value = value * 4
print(value)

value = value / 2
print(value)

Out [57] 10
7
28
14.0
```

If a function accepts multiple arguments, we must separate every two subsequent ones with a comma. Developers often add a space after the comma for readability.

When we pass the `print` function multiple arguments, it outputs all of them in sequence. In the next example, notice that Python separates the three printed elements with a space:

```
In [58] print("Cherry", "Strawberry", "Key Lime")

Out [58] Cherry Strawberry Key Lime
```

A *parameter* is a name given to an expected function argument. Each argument in an invocation corresponds to a parameter. In previous examples, we passed in arguments to the `print` function sequentially without specifying their parameter.

We have to write parameter names out explicitly for certain arguments. The `print` function's `sep` (separator) parameter, for example, customizes the string that Python inserts between every two printed values. We have to explicitly write out the `sep` parameter if we'd like to pass it a custom argument. We assign an argument to a function's keyword parameter with an equal sign. The next example outputs the same three strings but instructs the `print` function to separate them with exclamation points:

```
In [59] print("Cherry", "Strawberry", "Key Lime", sep = "!")

Out [59] Cherry!Strawberry!Key Lime
```

Let's come back to the example before the last one. Why were the three values printed with a space in between every two subsequent values?

A *default argument* is a fallback value that Python passes to a parameter if the function invocation does not explicitly provide one. The `sep` parameter to the `print` function has a default argument of `" "`. If we invoke the `print` function without an argument for the `sep` parameter, Python will automatically pass in a string with one space. The following two lines of code produce the same output:

```
In [60] # The two lines below are equivalent
        print("Cherry", "Strawberry", "Key Lime")
        print("Cherry", "Strawberry", "Key Lime", sep=" ")

Out [60] Cherry Strawberry Key Lime
        Cherry Strawberry Key Lime
```

We call parameters like `sep` *keyword arguments*. We have to write their specific parameter name when passing arguments to them. Python requires us to pass keyword arguments after sequential arguments. Here's another example of a `print` function invocation that passes a different string argument to the `sep` parameter:

```
In [61] print("Cherry", "Strawberry", "Key Lime", sep="*!*")  
Out [61] Cherry*!*Strawberry*!*Key Lime
```

The `print` function's `end` parameter customizes the string Python adds to the end of all output. The parameter's default argument is "`\n`", a special character that Python recognizes as a line break. In the next example, we explicitly pass the same "`\n`" argument to the `end` parameter:

```
In [62] print("Cherry", "Strawberry", "Key Lime", end="\n")  
       print("Peach Cobbler")  
  
Out [62] Cherry Strawberry Key Lime  
          Peach Cobbler
```

We can pass multiple keyword arguments to a function invocation. The technical rules still apply: separate every two arguments with a comma. The next example invokes the `print` function twice. The first invocation separates its three arguments with a "`!`" and ends the output with a "`****`". Because the first invocation does not force a line break, the second invocation's output continues where the first one concludes:

```
In [63] print("Cherry", "Strawberry", "Key Lime", sep="!", end="****")  
       print("Peach Cobbler")  
  
Out [63] Cherry!Strawberry!Key Lime****Peach Cobbler
```

Take a second to reflect on the code formatting in the preceding example. Long lines of code can be difficult to read, especially when we clump multiple parameters together. The Python community favors several formatting solutions. One option is placing all arguments on a separate line:

```
In [64] print(  
           "Cherry", "Strawberry", "Key Lime", sep="!", end="****"  
)  
  
Out [64] Cherry!Strawberry!Key Lime***
```

Another option is adding a line break between arguments:

```
In [65] print(  
           "Cherry",  
           "Strawberry",  
           "Key Lime",  
           sep="!",  
           end="****",  
)  
  
Out [65] Cherry!Strawberry!Key Lime***
```

All three of these code samples are technically valid. There are multiple ways to format Python code. I use several formatting options throughout the book. My ultimate goal is readability. You do not have to follow the formatting conventions I use. I will do my best to communicate which differences are technical and which ones are aesthetic.

B.4.2 Custom functions

We can declare custom functions in our programs. The goal of a function is to capture a distinct piece of business logic in a single, reusable procedure. A common mantra in software engineering circles is *DRY*, an acronym for *don't repeat yourself*. This acronym is a warning that duplication of the same logic or behavior can lead to an unstable program. The more places you repeat code, the more places you have to edit if requirements change. A function solves the DRY problem.

Let's explore an example. Suppose that we are meteorologists working with weather data. Our work requires us to convert temperatures in our program from Fahrenheit to Celsius. There is a simple, consistent formula to the conversion. Writing a function to convert *one* temperature from °F to °C is a good idea because we can isolate the conversion logic and reuse it as needed.

We begin a function definition with the `def` keyword. We follow `def` with the function's name, a pair of opening and closing parentheses, and a colon. Function names and variable names with multiple words follow a `snake_case` naming convention. The convention separates every two words with an underscore, which causes the name to resemble a snake. Let's call our function `convert_to_fahrenheit`:

```
def convert_to_fahrenheit():
```

To review, a *parameter* is a name for an expected function argument. We want the `convert_to_fahrenheit` function to accept a single parameter: a Celsius temperature. Let's call the parameter `celsius_temp`:

```
def convert_to_fahrenheit(celsius_temp):
```

If we define a parameter when we declare a function, we must pass an argument for that parameter when invoking it. Thus, we must always provide a value for `celsius_temp` whenever we run `convert_to_fahrenheit`.

Our next step is defining what the function does. We declare a function's steps in its body, an indented section of code below its name. Python uses indentation to establish relationships between constructs in the program. A function's body is an example of a *block*, a section of code nested within another section of code. According to PEP-8,¹ the Python community's style guide, we should indent each line in a block with four spaces:

```
def convert_to_fahrenheit(celsius_temp):
    # This indented line belongs to the function
    # So does this indented line

# This line is not indented, so it does not belong to convert_to_fahrenheit
```

¹ See “PEP 8—Style Guide for Python Code,” <https://www.python.org/dev/peps/pep-0008>.

We can use a function's parameters in its body. In our example, we can use the `celsius_temp` parameter anywhere in the body of the `convert_to_fahrenheit` function.

We can declare variables in a function body. These variables are called *local variables* because they are bound to the scope of the function execution. Python throws local variables out of memory as soon as the function is done running.

Let's write out the logic for the conversion! The formula to convert a Celsius temperature to Fahrenheit is to multiply it by 9/5 and add 32:

```
def convert_to_fahrenheit(celsius_temp):
    first_step = celsius_temp * (9 / 5)
    fahrenheit_temperature = first_step + 32
```

At this juncture, our function correctly calculates the Fahrenheit temperature, but it does not send the evaluation back to the main program. We need to use the `return` keyword to mark the Fahrenheit temperature as the final output of the function. We are returning it to the outside world:

```
In [66] def convert_to_fahrenheit(celsius_temp):
            first_step = celsius_temp * (9 / 5)
            fahrenheit_temperature = first_step + 32
            return fahrenheit_temperature
```

Our function is complete, so let's test it! We invoke custom functions with a pair of parentheses, the same syntax we use for Python's built-in functions. The next example invokes the `convert_to_fahrenheit` function with a sample argument of 10. Python runs through the function body with the `celsius_temp` parameter set to 10. The function returns a value of 50.0:

```
In [67] convert_to_fahrenheit(10)
Out [67] 50.0
```

We can provide keyword arguments instead of positional ones. The next example writes the `celsius_temp` parameter name out explicitly. The following code is equivalent to the preceding code:

```
In [68] convert_to_fahrenheit(celsius_temp = 10)
Out [68] 50.0
```

Although they are not required, keyword arguments help add clarity to our program. The preceding example better communicates what the `convert_to_fahrenheit` function's input represents.

B.5 Modules

A *module* is a single Python file. The Python *standard library* is a collection of more than 250 modules built into the language to accelerate productivity. The modules assist with technical operations such as mathematics, audio analysis, and URL requests. To

reduce a program's memory consumption, Python does not load these modules by default. We have to import the specific modules we want manually when our program requires them.

The syntax to import built-in modules and external packages is identical: enter the `import` keyword, followed by the module or package's name. Let's import Python's `datetime` module, which helps us work with dates and times:

```
In [69] import datetime
```

An *alias* is an alternative name for an import—a shortcut that we can assign to a module so we don't have to write out its complete name when we reference it. The alias is technically up to us, but certain nicknames have established themselves as favorites among Python developers. A popular alias for the `datetime` module, for example, is `dt`. We assign aliases with the `as` keyword:

```
In [70] import datetime as dt
```

Now we can reference the module with `dt` instead of `datetime`.

B.6 Classes and objects

All the data types that we've explored so far—integers, floats, Booleans, strings, exceptions, functions, and even modules—are objects. An *object* is a digital data structure, a container for storing, accessing, and manipulating a type of data.

A *class* is a blueprint for creating objects. Think of it as being a schematic or template from which Python builds the objects.

We call an object constructed from a class an *instance* of the class. The act of creating an object from a class is called *instantiation*.

Python's built-in `type` function returns the class of the object we pass in as an argument. The next example invokes the `type` function twice with two different strings: "peanut butter" and "jelly". Although their content is unequal, the strings are made from the same blueprint, the same class, the `str` class. They are both strings:

```
In [71] type("peanut butter")
```

```
Out [71] str
```

```
In [72] type("jelly")
```

```
Out [72] str
```

These examples are fairly simple. The `type` function is helpful when we are unsure what kind of object we're working with. If we invoke a custom function and are unsure what type of object it returns, we can pass its return value to `type` to find out.

A *literal* is a shorthand syntax that creates an object from a class. One example we've encountered so far is double quotes, which create strings ("hello"). For more-complex objects, we need to use a different creation process.

The `datetime` module we imported in section B.5 has a `date` class that models a date in time. Suppose that we’re trying to represent Leonardo da Vinci’s birthday, April 15, 1452, as a `date` object.

To create an instance from a class, write the class name followed by a pair of parentheses. `date()`, for example, creates a `date` object from the `date` class. The syntax is identical to invoking a function. When instantiating an object, we can sometimes pass arguments to the constructor, the function that creates the objects. The first three arguments to the `date` constructor represent the year, month, and day the `date` object will hold. The three arguments are required:

```
In [73] da_vinci_birthday = dt.date(1452, 4, 15)
         da_vinci_birthday
Out [73] datetime.date(1452, 4, 15)
```

Now we have a `da_vinci_birthday` variable that holds a `date` object representing April 15, 1452.

B.7 Attributes and methods

An *attribute* is a piece of internal data belonging to an object, a characteristic or detail that exposes information about the object. We access an object’s attributes with dot syntax. Three sample attributes on a `date` object are `day`, `month`, and `year`:

```
In [74] da_vinci_birthday.day
Out [74] 15
In [75] da_vinci_birthday.month
Out [75] 4
In [76] da_vinci_birthday.year
Out [76] 1452
```

A *method* is an action or command that we can issue to the object. Think of a method as being a function that belongs to an object. *Attributes* make up the object’s *state*, and methods represent the object’s behavior. Like a function, a method can accept arguments and produce a return value.

We invoke a method with a pair of parentheses after its name. Be sure to add a dot between the object and the method name. One sample method a `date` object has is `weekday`. The `weekday` method returns the date’s day of the week as an integer. 0 denotes Sunday, and 6 denotes Saturday:

```
In [77] da_vinci_birthday.weekday()
Out [77] 3
```

Leonardo was born on a Wednesday!

The easiness and reusability of methods such as `weekday` is why date objects exist. Imagine how difficult it would be to model date logic with a text string. Imagine if every developer built their own custom solution. Ouch. Python's developers anticipated that users would need to work with dates, so they built a reusable `date` class to model that real-world construct.

The key takeaway is that the Python standard library offers developers many utility classes and functions to solve common problems. As programs grow in complexity, however, it becomes difficult to model real-world ideas with only Python's core objects. To solve this problem, developers add custom objects to the language. These objects model business logic pertinent to a specific domain. Developers bundle these objects into libraries. That's all pandas is: a bundle of additional classes to solve specific problems in the domain of data analysis.

B.8 String methods

A string object has its own set of methods. Here are a few examples.

The `upper` method returns a new string with all characters in uppercase:

```
In [78] "Hello".upper()  
Out [78] "HELLO"
```

We can invoke methods on variables. Recall that a *variable* is a placeholder name for an object. Python will substitute the variable for the object that it references. The next example invokes the `upper` method on the string that the `greeting` variable references. The output is the same as that of the preceding code example:

```
In [79] greeting = "Hello"  
        greeting.upper()  
  
Out [79] "HELLO"
```

There are two categories of objects: mutable and immutable. A *mutable* object is capable of change. An *immutable* object is incapable of change. Strings, numbers, and Booleans are examples of immutable objects; we cannot modify them after we create them. The string "Hello" will always be the string "Hello". The number 5 will always be the number 5.

In the preceding example, the `upper` method call did not modify the original "Hello" string assigned to the `greeting` variable. Rather, the method invocation returned a new string with all capital letters. We can output the `greeting` variable to confirm that the characters have their original casing:

```
In [80] greeting  
Out [80] 'Hello'
```

A string is immutable, so its methods will not modify the original object. We'll explore some mutable objects starting in section B.9.

The complementary `lower` method returns a new string with all characters in lowercase:

```
In [81] "1611 BROADWAY".lower()  
Out [81] '1611 broadway'
```

There's even a `swapcase` method that returns a new string with each character case inverted. Uppercase letters become lowercase, and lowercase letters become uppercase:

```
In [82] "uPsIdE dOwN".swapcase()  
Out [82] 'UpSiDe DoWn'
```

A method can accept arguments. Let's take a peek at the `replace` method, which swaps all occurrences of a substring with a specified character sequence. The functionality is similar to the Find and Replace feature in a word processing program. The `replace` method accepts two arguments:

- The substring to look for
- The value to replace it with

The next example replaces all occurrences of "S" with "\$":

```
In [83] "Sally Sells Seashells by the Seashore".replace("S", "$")  
Out [83] '$ally $ells $eahells by the $eahore'
```

In this example,

- "Sally Sells Seashells by the Seashore" is the original string *object*.
- `replace` is the *method* invoked on the string.
- "S" is the *first argument* passed to the `replace` method invocation.
- "\$" is the *second argument* passed to the `replace` method invocation.
- "\$ally \$ells \$eahells by the \$eahore" is the *return value* of the `replace` method.

A method's return value can be of a different data type than the original object. The `isspace` method, for example, is invoked on a string but returns a Boolean. The method returns `True` if the string consists of only spaces; otherwise, it returns `False`.

```
In [84] " ".isspace()  
Out [84] True  
  
In [85] "3 Amigos".isspace()  
Out [85] False
```

Strings have a family of methods for removing whitespace. The `rstrip` (right strip) method removes whitespace from the end of a string:

```
In [86] data = " 10/31/2019 "  
       data.rstrip()  
  
Out [86] ' 10/31/2019 '
```

The `lstrip` (left strip) method removes whitespace from the beginning of a string:

```
In [87] data.lstrip()  
Out [87] '10/31/2019 '
```

The `strip` method removes whitespace from both ends of the string:

```
In [88] data.strip()  
Out [88] '10/31/2019'
```

The `capitalize` method capitalizes the first character of a string. This method often proves to be helpful for working with lowercase names, places, or organizations:

```
In [89] "robert".capitalize()  
Out [89] 'Robert'
```

The `title` method capitalizes the first letter of every word in a string, using a space to identify where each word begins and ends:

```
In [90] "once upon a time".title()  
Out [90] 'Once Upon A Time'
```

We can invoke multiple methods in sequence on a single line. This technique is called *method chaining*. In the next example, the `lower` method returns a new string object upon which we invoke the `title` method. The return value from `title` is yet another new string object:

```
In [91] "BENJAMIN FRANKLIN".lower().title()  
Out [91] 'Benjamin Franklin'
```

The `in` keyword checks whether a substring exists in another string. Enter the string to search for before the keyword and the string to search within after the keyword. The operation returns a Boolean:

```
In [92] "tuna" in "fortunate"  
Out [92] True  
In [93] "salmon" in "fortunate"  
Out [93] False
```

The `startswith` method checks whether a substring exists at the beginning of a string:

```
In [94] "factory".startswith("fact")  
Out [94] True
```

The `endswith` method checks whether a substring exists at the end of a string:

```
In [95] "garage".endswith("rage")  
Out [95] True
```

The `count` method counts the occurrences of a substring within a string. The next example counts the number of "e" characters in "celebrate":

```
In [96] "celebrate".count("e")  
Out [96] 3
```

The `find` and `index` methods locate the index position of a character or substring. The methods return the first index position at which the argument occurs. Recall that index positions start counting at 0. The next example searches for the index of the first "e" in "celebrate". Python locates it at index 1:

```
In [97] "celebrate".find("e")  
Out [97] 1  
In [98] "celebrate".index("e")  
Out [98] 1
```

What's the difference between the `find` and `index` methods? If the string does not contain the argument, `find` will return -1, and `index` will raise a `ValueError` exception:

```
In [99] "celebrate".find("z")  
Out [99] -1  
In [100] "celebrate".index("z")  
-----  
ValueError                                                 Traceback (most recent call last)  
<ipython-input-5-bf78a69262aa> in <module>  
----> 1 "celebrate".index("z")  
  
ValueError: substring not found
```

Each method exists for a specific situation; neither option is better than the other. If your program depends on a substring existing within a larger string, for example, you may use the `index` method and react to the error. By comparison, if the absence of a substring does not prohibit your program from executing, you can use the `find` method to avoid crashing.

B.9 Lists

A *list* is a container for storing objects in order. The purpose of lists is twofold: to provide a “box” to store values and to keep them in sequence. We refer to the items within a list as *elements*. In other programming languages, this data structure is often called an *array*.

We declare a list with a pair of opening and closing square brackets. We write our elements inside the square brackets, separating every two with a comma. The next example creates a list of five strings:

```
In [101] backstreet_boys = ["Nick", "AJ", "Brian", "Howie", "Kevin"]
```

The length of a list is equal to its number of elements. Remember the trusty `len` function? It can help us figure how many members are in the greatest boy band of all time:

```
In [102] len(backstreet_boys)  
Out [102] 5
```

An *empty list* is a list without elements. It has a length of 0:

```
In [103] []  
Out [103] []
```

A list can store elements of any data type: strings, numbers, floats, Booleans, and more. A *homogeneous* list is one in which all elements have the same type. The following three lists are homogeneous. The first holds integers, the second holds floating-points, and the third holds Booleans:

```
In [104] prime_numbers = [2, 3, 5, 7, 11]  
In [105] stock_prices_for_last_four_days = [99.93, 105.23, 102.18, 94.45]  
In [106] settings = [True, False, False, True, True, False]
```

Lists can also store elements of different data types. A *heterogeneous* list is one in which elements have different data types. The following list has a string, an integer, a Boolean, and a floating-point number:

```
In [107] motley_crew = ["rhinoceros", 42, False, 100.05]
```

Much as it does for each character in a string, Python assigns each list element an index position. The index represents an element's place in line and starts counting from 0. In the following three-item `favorite_foods` list,

- "Sushi" occupies index position 0.
- "Steak" occupies index position 1.
- "Barbeque" occupies index position 2.

```
In [108] favorite_foods = ["Sushi", "Steak", "Barbeque"]
```

Two quick notes on list formatting. First, Python permits us to insert a comma after a list's last element. The comma does not affect the list whatsoever; it is an alternative syntax:

```
In [109] favorite_foods = ["Sushi", "Steak", "Barbeque", ]
```

Second, some Python style guides recommend breaking up long lists so that each element occupies a single line. This format also does not affect the list in any technical way. The syntax looks like this:

```
In [110] favorite_foods = [  
    "Sushi",  
    "Steak",  
    "Barbeque",  
]
```

Throughout the examples in this book, I've used whatever formatting style I believe best enhances readability. You are welcome to use whichever format feels best to you.

We can access a list element by its index position. Pass the index between a pair of square brackets after the list (or the variable that references it):

```
In [111] favorite_foods[1]  
Out [111] 'Steak'
```

In section B.1.2, we introduced a slicing syntax to extract characters from a string. We can use the same syntax to extract elements from a list. The next example pulls out the elements from index positions 1 to 3. Remember that in a list slice, the starting index is inclusive, and the ending index is exclusive:

```
In [112] favorite_foods[1:3]  
Out [112] ['Steak', 'Barbeque']
```

We can remove the number before the colon to pull from the beginning of the list. The next example extracts elements from the start of the list to index 2 (exclusive):

```
In [113] favorite_foods[:2]  
Out [113] ['Sushi', 'Steak']
```

We can remove the number after the colon to pull to the end of the list. The next example extracts elements from index 2 to the end of the list:

```
In [114] favorite_foods[2:]  
Out [114] ['Barbeque']
```

Leave out both numbers to create a copy of the list:

```
In [115] favorite_foods[:]  
Out [115] ['Sushi', 'Steak', 'Barbeque']
```

Finally, we can provide an optional third number in the square brackets to extract elements in intervals. The next example pulls elements from index position 0 (inclusive) to index position 3 (exclusive) in increments of 2:

```
In [116] favorite_foods[0:3:2]  
Out [116] ['Sushi', 'Barbeque']
```

All slicing options return a new list.

Let's walk through some list methods. The `append` method adds a new element to the end of a list:

```
In [117] favorite_foods.append("Burrito")  
favorite_foods  
Out [117] ['Sushi', 'Steak', 'Barbeque', 'Burrito']
```

Do you recall our discussion on mutability versus immutability? A list is an example of a mutable object, an object that is *capable* of change. We can add, remove, or replace elements within a list after we create it. In the preceding example, the `append` method mutated the list referenced by the `favorite_foods` variable. We did not create a new list.

By comparison, a string is an example of an immutable object. When we invoke a method like `upper`, Python returns a new string; the original string remains unaffected. Immutable objects cannot change.

Lists include a variety of mutational methods. The `extend` method adds multiple elements to the end of a list. It accepts one argument, a list with the values to add:

```
In [118] favorite_foods.extend(["Tacos", "Pizza", "Cheeseburger"])
         favorite_foods

Out [118] ['Sushi', 'Steak', 'Barbeque', 'Burrito', 'Tacos', 'Pizza',
           'Cheeseburger']
```

The `insert` method adds an element to the list at a specific index position. Its first argument is the index where we want to inject the element, and its second argument is the new element. Python pushes values at and after the specified index position to the next slot. The next example inserts the string "Pasta" at index position 2. The list shifts the value "Barbeque" and all subsequent elements up one index position:

```
In [119] favorite_foods.insert(2, "Pasta")
         favorite_foods

Out [119] ['Sushi',
           'Steak',
           'Pasta',
           'Barbeque',
           'Burrito',
           'Tacos',
           'Pizza',
           'Cheeseburger']
```

The `in` keyword can check whether a list includes an element. "Pizza" exists in our `favorite_foods` list, and "Caviar" does not:

```
In [120] "Pizza" in favorite_foods
Out [120] True

In [121] "Caviar" in favorite_foods
Out [121] False
```

The `not in` operator confirms the absence of an element from a list. It returns the inverse Boolean of the `in` operator:

```
In [122] "Pizza" not in favorite_foods
Out [122] False
```

```
In [123] "Caviar" not in favorite_foods
Out [123] True
```

The `count` method counts the number of times an element appears in the list:

```
In [124] favorite_foods.append("Pasta")
favorite_foods

Out [124] ['Sushi',
           'Steak',
           'Pasta',
           'Barbeque',
           'Burrito',
           'Tacos',
           'Pizza',
           'Cheeseburger',
           'Pasta']

In [125] favorite_foods.count("Pasta")

Out [125] 2
```

The `remove` method deletes the first occurrence of an element from the list. Note that Python does not remove subsequent occurrences of the element:

```
In [126] favorite_foods.remove("Pasta")
favorite_foods

Out [126] ['Sushi',
           'Steak',
           'Barbeque',
           'Burrito',
           'Tacos',
           'Pizza',
           'Cheeseburger',
           'Pasta']
```

Let's get rid of the other "Pasta" string at the end of the list. The `pop` method removes and returns the last element from the list:

```
In [127] favorite_foods.pop()

Out [127] 'Pasta'

In [128] favorite_foods

Out [128] ['Sushi', 'Steak', 'Barbeque', 'Burrito', 'Tacos', 'Pizza',
           'Cheeseburger']
```

The `pop` method also accepts an integer argument with the index position of the value Python should delete. The next example removes the "Barbeque" value at index position 2. The "Burrito" string slides into index position 2, and the elements after it also shift down by one index:

```
In [129] favorite_foods.pop(2)

Out [129] 'Barbeque'
```

```
In [130] favorite_foods
Out [130] ['Sushi', 'Steak', 'Burrito', 'Tacos', 'Pizza', 'Cheeseburger']
```

A list can hold any object, including other lists. The next example declares a list with three nested lists. Each nested list contains three integers:

```
In [131] spreadsheet = [
    [1, 2, 3],
    [4, 5, 6],
    [7, 8, 9]
]
```

Let's take a second to reflect on the preceding visual. Can you see any parallels with a spreadsheet? A nested list is one way we can represent a multidimensional, tabular collection of data. We can view the outermost list as being a worksheet and each internal list as being a row of data.

B.9.1 List iteration

A list is an example of a collection object. It is capable of storing multiple values—a *collection* of values. To *iterate* means to move over a collection object’s elements one at a time.

The most common way to iterate over a list’s items is with a `for` loop. Its syntax looks like this:

```
for variable_name in some_list:
    # Do something
```

A `for` loop consists of several components:

- The `for` keyword.
- A variable name that will store each list element one at a time as the iteration runs.
- The `in` keyword.
- The list to iterate over.
- A block of code that Python will run during each iteration. We can use the variable name in this block of code.

As a reminder, a *block* is a section of indented code. Python uses indentation to associate constructs in our program. The block below a function name defines what the function does. Similarly, the block below a `for` loop defines what happens during each iteration.

The next example iterates over a list of four strings, printing the length of each one:

```
In [132] for season in ["Winter", "Spring", "Summer", "Fall"]:
    print(len(season))

Out [132] 6
        6
        6
        4
```

The preceding iteration consists of four loops. The `season` variable holds the values "Winter", "Spring", "Summer", and "Fall" in sequence. During each iteration, we pass the current string to the `len` function. The `len` function returns a number, which we print out.

Suppose that we want to add the lengths of the strings together. We have to combine a `for` loop with some other Python concepts. In the next example, we first initialize a `letter_count` variable to hold a cumulative sum. Inside the `for` loop block, we calculate the length of the current string with the `len` function and then overwrite the running total. Finally, we output the value of `letter_count` after the loop completes:

```
In [133] letter_count = 0

for season in ["Winter", "Spring", "Summer", "Fall"]:
    letter_count = letter_count + len(season)

letter_count

Out [133] 22
```

The `for` loop is the most conventional option for iterating over a list. Python also supports another syntax, which we discuss in section B.9.2.

B.9.2 *List comprehension*

List comprehension is a shorthand syntax to create a list from a collection object. Suppose that we have a list of six numbers:

```
In [134] numbers = [4, 8, 15, 16, 23, 42]
```

Let's say that we want to create a new list with the squares of those numbers. In other words, we want to apply a consistent operation to each element in the original list. One solution is to iterate over each integer in `numbers`, take its square, and add the result to a new list. As a reminder, the `append` method adds an element to the end of a list:

```
In [135] squares = []

for number in numbers:
    squares.append(number ** 2)

squares

Out [135] [16, 64, 225, 256, 529, 1764]
```

List comprehension can produce the same list of squares in a single line of code. Its syntax requires a pair of opening and closing square brackets. Inside the brackets, we first describe what we'd like to do with each element we iterate over and then the collection from which the iterable items will come.

The next example still iterates over the `numbers` list and assigns each list element to a `number` variable. We declare what we'd like to do with each number before the

for keyword. We move the number `** 2` calculation to the beginning and the for in logic to the end:

```
In [136] squares = [number ** 2 for number in numbers]
squares
```

```
Out [136] [16, 64, 225, 256, 529, 1764]
```

List comprehension is considered to be the more Pythonic way to create a new list from an existing data structure. The *Pythonic way* describes the collection of recommended practices adopted by Python developers over time.

B.9.3 Converting a string to a list and vice versa

We're familiar with lists and strings now, so let's see how we can use them together. Suppose that we have a string in our program that holds an address:

```
In [137] empire_state_bldg = "20 West 34th Street, New York, NY, 10001"
```

What if we want to break the address into smaller components: street, city, state, and zip code? Notice that the string uses a comma to separate the four pieces.

A string's `split` method breaks a string apart by using a *delimiter*, a sequence of one or more characters marking a boundary. The next example asks the `split` method to split `empire_state_building` on every occurrence of a comma. The method returns a list consisting of the smaller strings:

```
In [138] empire_state_bldg.split(",")
```

```
Out [138] ['20 West 34th Street', ' New York', ' NY', ' 10001']
```

This code is a step in the right direction. But notice that the last three elements in the list have a leading space. Although we could iterate over the list's elements and call the `strip` on each one to remove its whitespace, a more optimal solution is to add the space to the `split` method's delimiter argument:

```
In [139] empire_state_bldg.split(", ")
```

```
Out [139] ['20 West 34th Street', 'New York', 'NY', '10001']
```

We've successfully broken the string into a list of strings.

The process also works in reverse. Suppose that we stored our address in a list and want to concatenate the list's elements into a single string:

```
In [140] chrysler_bldg = ["405 Lexington Ave", "New York", "NY", "10174"]
```

First, we must declare the string that we'd like Python to inject between every two list elements. Then we can invoke the `join` method on the string and pass in a list as the argument. Python will join the list's elements, separating each two with the delimiter. The next example uses a delimiter of a comma and a space:

```
In [141] ", ".join(chrysler_bldg)
```

```
Out [141] '405 Lexington Ave, New York, NY, 10174'
```

The `split` and `join` methods are helpful for working with text data, which often needs to be separated and remerged.

B.10 Tuples

A *tuple* is a similar data structure to a Python list. A tuple also stores elements in order, but unlike a list, it is immutable. We cannot add, remove, or replace elements within the tuple after we create it.

The only technical requirement for defining a tuple is to declare multiple elements and separate every subsequent two with a comma. The following example declares a three-element tuple:

```
In [142] "Rock", "Pop", "Country"  
Out [142] ('Rock', 'Pop', 'Country')
```

Usually, however, we declare a tuple with a pair of parentheses. The syntax makes it easier to identify the object visually:

```
In [143] music_genres = ("Rock", "Pop", "Country")  
music_genres  
Out [143] ('Rock', 'Pop', 'Country')
```

The `len` function returns the length of a tuple:

```
In [144] len(music_genres)  
Out [144] 3
```

To declare a tuple with one element, we must include a comma after the element. Python needs the comma to identify the tuple. Compare the differences in the next two outputs. The first example does not use a comma; Python reads the value as a string.

```
In [145] one_hit_wonders = ("Never Gonna Give You Up")  
one_hit_wonders  
Out [145] 'Never Gonna Give You Up'
```

By comparison, the syntax here returns a tuple. Yes, one symbol can make a world of difference in Python:

```
In [146] one_hit_wonders = ("Never Gonna Give You Up",)  
one_hit_wonders  
Out [146] ('Never Gonna Give You Up',)
```

Use the `tuple` function to create an *empty tuple*, which is one without elements:

```
In [147] empty_tuple = tuple()  
empty_tuple  
Out [147] ()  
In [148] len(empty_tuple)  
Out [148] 0
```

As with a list, you can access tuple elements by index position. As with a list, you can iterate over tuple elements with a `for` loop. The only thing you can't do is modify the tuple. Because of its immutability, a tuple doesn't include mutational methods such as `append`, `pop`, and `insert`.

If you have a collection of elements in order, and you know that it will not change, you can prefer a tuple over a list to store it.

B.11 Dictionaries

Lists and tuples are optimal data structures for storing objects in order. We need another data structure to solve a different kind of problem: establishing associations between objects.

Consider a restaurant menu. Each menu item is a unique identifier that we use to look up a corresponding price. The menu item and its cost are associated. The order of items is not what's important; it's the *connection* between two pieces of data.

A *dictionary* is a mutable, unordered collection of key-value pairs. A pair consists of a key and a value. Each key serves as an identifier for a value. Keys must be unique. Values can contain duplicates.

We declare a dictionary with a pair of curly braces (`{}`). The following example creates an empty dictionary:

```
In [149] {}
```

```
Out [149] {}
```

Let's model a sample restaurant menu in Python. Inside the curly braces, we assign a key to its value with a colon (`:`). The following example declares a dictionary with one key-value pair. The string key "Cheeseburger" is assigned the floating-point value 7.99:

```
In [150] { "Cheeseburger": 7.99 }
```

```
Out [150] {'Cheeseburger': 7.99}
```

When declaring a dictionary with multiple key-value pairs, separate every two pairs with a comma. Let's expand our menu dictionary to hold three key-value pairs. Notice that the values for the "French Fries" and "Soda" keys are identical:

```
In [151] menu = {"Cheeseburger": 7.99, "French Fries": 2.99, "Soda": 2.99}  
menu
```

```
Out [151] {'Cheeseburger': 7.99, 'French Fries': 2.99, 'Soda': 2.99}
```

We can count the number of key-value pairs in a dictionary by passing it to Python's built-in `len` function:

```
In [152] len(menu)
```

```
Out [152] 3
```

We use keys to retrieve values from dictionaries. Place a pair of square brackets with the key immediately after the dictionary. The syntax is identical to accessing a list element by index position. The following example extracts the value for the "French Fries" key:

```
In [153]: menu["French Fries"]  
Out [153]: 2.99
```

In a list, the index position is always a number. In a dictionary, a key can be any immutable data type: integers, floats, strings, Booleans, and more.

Python raises a `KeyError` exception if the key does not exist in the dictionary. `KeyError` is another example of a native Python error:

```
In [154]: menu["Steak"]  
  
-----  
KeyError Traceback (most recent call last)  
<ipython-input-19-0ad3e3ec4cd7> in <module>  
----> 1 menu["Steak"]  
  
KeyError: 'Steak'
```

As always, case sensitivity matters. If a single character is mismatched, Python will not be able to find a key. The key "soda" does not exist in our dictionary. Only "Soda" does:

```
In [155]: menu["soda"]  
  
-----  
KeyError Traceback (most recent call last)  
<ipython-input-20-47940ceca824> in <module>  
----> 1 menu["soda"]  
  
KeyError: 'soda'
```

The `get` method also extracts a dictionary value by using a key:

```
In [156]: menu.get("French Fries")  
Out [156]: 2.99
```

The `get` method's advantage is that it returns `None` if the key does not exist rather than raise an error. Remember that `None` is an object that Python uses to represent the idea of absence or nullness. The `None` value produces no visual output in Jupyter Notebook. But we can wrap the invocation in a `print` function to force Python to print `None`'s string representation:

```
In [157]: print(menu.get("Steak"))  
Out [157]: None
```

The second argument to the `get` method is a custom value to return if the key does not exist in the dictionary. In the next example, the string "Steak" does not exist as a key in the `menu` dictionary, so Python returns `99.99` instead:

```
In [158] menu.get("Steak", 99.99)  
Out [158] 99.99
```

A dictionary is a mutable data structure. We can add key-value pairs to or remove key-value pairs from the dictionary after we create it. To add a new key-value pair, provide the key in square brackets, and assign a value to it with the assignment operator (=):

```
In [159] menu["Taco"] = 0.99  
menu  
Out [159] {'Cheeseburger': 7.99, 'French Fries': 2.99, 'Soda': 1.99,  
'Taco': 0.99}
```

If the key already exists in the dictionary, Python will overwrite its original value. The next example changes the value of the "Cheeseburger" key from 7.99 to 9.99:

```
In [160] print(menu["Cheeseburger"])  
menu["Cheeseburger"] = 9.99  
print(menu["Cheeseburger"])  
  
Out [160] 7.99  
9.99
```

The `pop` method removes a key-value pair from a dictionary; it accepts a key as an argument and returns its value. Python will raise a `KeyError` exception if the key does not exist in the dictionary:

```
In [161] menu.pop("French Fries")  
Out [161] 2.99  
  
In [162] menu  
Out [162] {'Cheeseburger': 9.99, 'Soda': 1.99, 'Taco': 0.99}
```

The `in` keyword checks whether an element exists in the dictionary's keys:

```
In [163] "Soda" in menu  
Out [163] True  
  
In [164] "Spaghetti" in menu  
Out [164] False
```

To check for inclusion among the dictionary's values, invoke the `values` method on the dictionary. The method returns a listlike object that contains the dictionary's values. We can use the `in` operator in combination with the `values` method's return value:

```
In [165] 1.99 in menu.values()  
Out [165] True  
  
In [166] 499.99 in menu.values()  
Out [166] False
```

The `values` method returns a different type of object from the lists, tuples, and dictionaries we've already seen. We don't necessarily need to know what the object is, however. All we care about is how we can work with it. The `in` operator checks for the inclusion of a value in an object, and the object returned by the `values` method knows how to handle it.

B.11.1 Dictionary Iteration

We should always assume that a dictionary's key-value pairs are unordered. If you need a data structure that maintains order, use a list or a tuple. If you need to create associations between objects, use a dictionary.

Even if we cannot guarantee a deterministic iteration order, we can still loop over a dictionary one key-value pair at a time with a `for` loop. The dictionary's `items` method yields a two-item tuple on each iteration. The tuple holds a key and its respective value. We can declare multiple variables after the `for` keyword to store each key and value. In the next example, the `state` variable holds each dictionary key, and the `capital` variable holds each value:

```
In [167] capitals = {  
    "New York": "Albany",  
    "Florida": "Tallahassee",  
    "California": "Sacramento"  
}  
  
for state, capital in capitals.items():  
    print("The capital of " + state + " is " + capital + ".")  
  
The capital of New York is Albany.  
The capital of Florida is Tallahassee.  
The capital of California is Sacramento.
```

In the first iteration, Python yields a tuple of (`"New York"`, `"Albany"`). In the second iteration, it yields a tuple of (`"Florida"`, `"Tallahassee"`), and so on.

B.12 Sets

List and dictionary objects help solve the problems of order and association. A set assists with another common need: uniqueness. A *set* is an unordered, mutable collection of unique elements. It prohibits duplicates.

We declare a set with a pair of curly braces. We populate the braces with elements, separating every two with a comma. The next example declares a set of six numbers:

```
In [168] favorite_numbers = { 4, 8, 15, 16, 23, 42 }
```

Readers with a sharp eye may notice that the curly-brace syntax for declaring a set is identical to the syntax for declaring a dictionary. Python can distinguish between the two types of objects based on the presence or absence of key-value pairs.

Because Python interprets an empty pair of curly braces as an empty dictionary, the only way to create an empty set is with the built-in `set` function:

```
In [169] set()  
Out [169] set()
```

Here are some helpful set methods. The `add` method adds a new element to the set:

```
In [170] favorite_numbers.add(100)  
favorite_numbers  
Out [170] {4, 8, 15, 16, 23, 42, 100}
```

Python will add an element to a set only if the set does not already have it. The next example attempts to add 15 to `favorite_numbers`. Python sees that 15 already exists within the set, so the object remains unchanged:

```
In [171] favorite_numbers.add(15)  
favorite_numbers  
Out [171] {4, 8, 15, 16, 23, 42, 100}
```

A set has no concept of order. Python will raise a `TypeError` exception if we attempt to access a set element by index position:

```
In [172] favorite_numbers[2]  
-----  
TypeError Traceback (most recent call last)  
<ipython-input-17-e392cd51c821> in <module>  
----> 1 favorite_numbers[2]  
  
TypeError: 'set' object is not subscriptable
```

Python raises a `TypeError` exception when we attempt to apply an operation to an invalid object. Set elements are unordered, so elements do not have index positions.

In addition to preventing duplicates, sets are ideal for identifying similarities and differences between two collections of data. Let's define two sets of strings:

```
In [173] candy_bars = { "Milky Way", "Snickers", "100 Grand" }  
sweet_things = { "Sour Patch Kids", "Reeses Pieces", "Snickers" }
```

The `intersection` method returns a new set with elements found in both of the original sets. The `&` symbol performs the same logic. In the next example, "Snickers" is the only string in common between `candy_bars` and `sweet_things`:

```
In [174] candy_bars.intersection(sweet_things)  
Out [174] {'Snickers'}  
In [175] candy_bars & sweet_things  
Out [175] {'Snickers'}
```

The `union` method returns a set that combines all elements of the two sets. The `|` symbol performs the same logic. Keep in mind that duplicate values such as "Snickers" will appear only once:

```
In [176] candy_bars.union(sweet_things)

Out [176] {'100 Grand', 'Milky Way', 'Reeses Pieces', 'Snickers', 'Sour
Patch Kids'}

In [177] candy_bars | sweet_things

Out [177] {'100 Grand', 'Milky Way', 'Reeses Pieces', 'Snickers', 'Sour
Patch Kids'}
```

The `difference` method returns a set of elements that are present in the set the method is called on but not present in the set passed in as an argument. We can use the `-` symbol as a shortcut. In the next example, "100 Grand" and "Milky Way" are present in `candy_bars` but not in `sweet_things`:

```
In [178] candy_bars.difference(sweet_things)

Out [178] {'100 Grand', 'Milky Way'}

In [179] candy_bars - sweet_things

Out [179] {'100 Grand', 'Milky Way'}
```

The `symmetric_difference` method returns a set with elements found in either of the sets but not both. The `^` syntax accomplishes the same result:

```
In [180] candy_bars.symmetric_difference(sweet_things)

Out [180] {'100 Grand', 'Milky Way', 'Reeses Pieces', 'Sour Patch Kids'}

In [181] candy_bars ^ sweet_things

Out [181] {'100 Grand', 'Milky Way', 'Reeses Pieces', 'Sour Patch Kids'}
```

And that's all there is to cover! We've learned quite a bit of Python: data types, functions, iterations, and more. It's OK if you don't remember all the details. Rather, come back to this appendix whenever you need a refresher on the core mechanics of Python. We'll be using and reviewing a lot of these ideas as we work with the pandas library.

appendix C

NumPy crash course

The open source NumPy (Numerical Python) library is a dependency of pandas that exposes a powerful `ndarray` object for storing homogeneous, *n*-dimensional arrays. That's quite a mouthful, so let's break it down. An *array* is an ordered collection of values akin to a Python list. *Homogeneous* means that the values within the array are of the same data type. *N-dimensional* means that the array can hold any number of dimensions. (We'll talk about dimensions in section C.1.) NumPy was developed by data scientist Travis Oliphant, who founded Anaconda, the company that builds the Python distribution we used to set up our development environment.

We can use NumPy to generate randomized data sets of any size and shape; in fact, the official pandas documentation does so extensively. Basic knowledge of the library will help enhance our understanding of the underlying mechanics of pandas.

C.1 Dimensions

Dimensions refers to the number of reference points needed to extract a single value from a data structure. Consider a collection of temperatures across several cities on a given day:

| | Temperature |
|---------------|--------------------|
| New York | 38 |
| Chicago | 36 |
| San Francisco | 51 |
| Miami | 73 |

If I asked you to find a specific temperature in this data set, you'd need only one point of reference: the city's name (such as "San Francisco") or its order (such as "the third city in the list"). Thus, the table depicts a one-dimensional data set.

Compare that table with a data set of temperatures for multiple cities over multiple days:

| | Monday | Tuesday | Wednesday | Thursday | Friday |
|---------------|--------|---------|-----------|----------|--------|
| New York | 38 | 41 | 35 | 32 | 35 |
| Chicago | 36 | 39 | 31 | 27 | 25 |
| San Francisco | 51 | 52 | 50 | 49 | 53 |
| Miami | 73 | 74 | 72 | 71 | 74 |

How many points of reference do you need now to extract a specific value from this data set? The answer is 2. We need a city and a day of the week (such as “San Francisco on Thursday”) or a row number and a column number (such as “row 3 and column 4”). Neither the city nor the weekday is a sufficient identifier by itself, because each one associates with multiple values in the data set. The combination of a city and a weekday (or, equivalently, a row and a column) filters the results down to one value; thus, this data set is two-dimensional.

A data set’s number of rows and columns does not affect its number of dimensions. A table with 1 million rows and 1 million columns would still be two-dimensional. We would still need a combination of a row position and a column position to pull out a value.

Every additional point of reference adds another dimension. We might collect temperatures over two weeks:

Week 1

| | Monday | Tuesday | Wednesday | Thursday | Friday |
|---------------|--------|---------|-----------|----------|--------|
| New York | 38 | 41 | 35 | 32 | 35 |
| Chicago | 36 | 39 | 31 | 27 | 25 |
| San Francisco | 51 | 52 | 50 | 49 | 53 |
| Miami | 73 | 74 | 72 | 71 | 74 |

Week 2

| | Monday | Tuesday | Wednesday | Thursday | Friday |
|---------------|--------|---------|-----------|----------|--------|
| New York | 40 | 42 | 38 | 36 | 28 |
| Chicago | 32 | 28 | 25 | 31 | 25 |
| San Francisco | 49 | 55 | 54 | 51 | 48 |
| Miami | 75 | 78 | 73 | 76 | 71 |

The city and weekday are no longer sufficient to extract a single value. We now need three points of reference (Week, City, and Day), so we can classify this data set as being three-dimensional.

C.2 The ndarray object

Let's begin by creating a new Jupyter Notebook and importing the NumPy library, which is typically assigned the alias np:

```
In [1] import numpy as np
```

NumPy excels at generating both random and nonrandom data. Let's begin with a simple challenge: creating a sequential range of numbers.

C.2.1 Generating a numeric range with the arange method

The arange function returns a one-dimensional ndarray object with a range of sequential numeric values. When we invoke arange with one argument, NumPy will set 0 as the lower bound, the value at which the range begins. The first argument will set the upper bound, the number at which the range terminates. The upper bound is exclusive; NumPy will go up to that value but not include it. An argument of 3, for example, will produce an ndarray holding the values 0, 1, and 2:

```
In [2] np.arange(3)  
Out [2] array([0, 1, 2])
```

We can also pass arange two arguments, which will declare the lower and upper bounds of the range. The lower bound is inclusive; the range will include its value. The endpoint remains exclusive. In the next example, notice that NumPy includes 2 but not 6:

```
In [3] np.arange(2, 6)  
Out [3] array([2, 3, 4, 5])
```

The first two arguments to arange correspond to start and stop keyword parameters. We can write the keyword arguments out explicitly. The preceding and following code samples produce the same array:

```
In [4] np.arange(start = 2, stop = 6)  
Out [4] array([2, 3, 4, 5])
```

The arange function's optional third parameter, step, sets the interval between every two values. It helps to think about this concept mathematically. Start at the lower bound, and add the interval value until you reach the upper bound. The next example creates a range from 0 to 111 (exclusive) in gaps of 10:

```
In [5] np.arange(start = 0, stop = 111, step = 10)  
Out [5] array([ 0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110])
```

Let's save that last ndarray to a tens variable:

```
In [6] tens = np.arange(start = 0, stop = 111, step = 10)
```

Now the tens variable points to an ndarray object that holds 12 numbers.

C.2.2 Attributes on a ndarray object

The NumPy library's ndarray object has its own set of attributes and methods. As a reminder, an *attribute* is a piece of data that belongs to an object. A *method* is a command we can send to an object.

The shape attribute returns a tuple with the array's dimensions. The length of the shape tuple is equal to the ndarray's number of dimensions. The following output communicates that tens is a one-dimensional array with 12 values:

```
In [7] tens.shape
```

```
Out [7] (12,)
```

We can also ask for the ndarray's number of dimensions with the ndim attribute:

```
In [8] tens.ndim
```

```
Out [8] 1
```

The size attribute returns the number of elements in the array:

```
In [9] tens.size
```

```
Out [9] 12
```

Next up, let's see how we can manipulate the shape of the 12 elements in the array.

C.2.3 The reshape method

Currently, our 12-element tens ndarray is one-dimensional. We can access any element with one reference point, its position in the array:

```
In [10] tens
```

```
Out [10] array([ 0,  10,  20,  30,  40,  50,  60,  70,  80,  90, 100,
 110])
```

We may want to manipulate an existing one-dimensional array into a multidimensional one with a different shape. Let's say that our 12 values represent a collection of 3 daily measurements captured across 4 days. It's easier to think about the data in a 4 x 3 shape than in a 12 x 1 shape.

The reshape method uses its arguments to return a new ndarray object with a specified shape. The next example contorts tens into a new two-dimensional array with 4 rows and 3 columns:

```
In [11] tens.reshape(4, 3)

Out [11] array([[ 0, 10, 20],
   [ 30, 40, 50],
   [ 60, 70, 80],
   [ 90, 100, 110]])
```

The number of arguments passed to `reshape` will equal the number of dimensions in the new ndarray:

```
In [12] tens.reshape(4, 3).ndim

Out [12] 2
```

We must ensure that the product of the arguments equals the number of elements within the original array. The values 4 and 3 are valid arguments because their product is 12, and `tens` has 12 values. Another valid example is a two-dimensional array with 2 rows and 6 columns:

```
In [13] tens.reshape(2, 6)

Out [13] array([[ 5, 15, 25, 35, 45, 55],
   [ 65, 75, 85, 95, 105, 115]])
```

NumPy raises a `ValueError` exception if it cannot contort the original array into the requested shape. In the next example, the library is unable to fit the 12 values in `tens` into a 2 x 5 array:

```
In [14] tens.reshape(2, 5)

Out [14]

-----
ValueError                                                 Traceback (most recent call last)
<ipython-input-68-5b9588276555> in <module>
----> 1 tens.reshape(2, 5)

ValueError: cannot reshape array of size 12 into shape (2,5)
```

Can an ndarray store more than two dimensions of data? Absolutely. Let's provide a third argument to `reshape` to see it in action. The next example shapes the one-dimensional `tens` array into a three-dimensional array with a 2 x 3 x 2 shape:

```
In [15] tens.reshape(2, 3, 2)

Out [15] array([[[ 5, 15],
   [ 25, 35],
   [ 45, 55]],

   [[ 65, 75],
   [ 85, 95],
   [105, 115]]])
```

Let's access the `ndim` attribute on the new array. The data structure does indeed have three dimensions:

```
In [16] tens.reshape(2, 3, 2).ndim  
Out [16] 3
```

We can also pass an argument of `-1` to `reshape` to denote an unknown dimension. NumPy will infer the correct number of values to populate within that dimension. The next example passes arguments of `2` and `-1`. NumPy calculates that the new two-dimensional array should have a `2 x 6` shape:

```
In [17] tens.reshape(2, -1)  
Out [17] array([[ 0, 10, 20, 30, 40, 50],  
 [ 60, 70, 80, 90, 100, 110]])
```

In the next example, the library calculates that the returned `ndarray` should have a `2 x 3 x 2` shape:

```
In [18] tens.reshape(2, -1, 2)  
Out [18] array([[[ 0, 10],  
 [ 20, 30],  
 [ 40, 50]],  
  
 [[ 60, 70],  
 [ 80, 90],  
 [100, 110]]])
```

We can pass only one unknown dimension into a `reshape` method invocation.

The `reshape` method returns a new `ndarray` object. The original array is not mutated. Thus, our `tens` array still has its original `1 x 12` shape.

C.2.4 The `randint` function

The `randint` function generates one or more random numbers between a range. When passed a single argument, it returns a random integer from `0` up to the value. The next example returns a random value between `0` and `5` (exclusive):

```
In [19] np.random.randint(5)  
Out [19] 3
```

We can pass `randint` two arguments to declare an inclusive lower bound and an exclusive upper bound. NumPy will select a number from within the range:

```
In [20] np.random.randint(1, 10)  
Out [20] 9
```

What if we want to generate an array of random integers? We can pass a third argument to `randint` to specify the desired array shape. We can pass either a single integer or a one-element list to create a one-dimensional array:

```
In [21] np.random.randint(1, 10, 3)

Out [21] array([4, 6, 3])

In [22] np.random.randint(1, 10, [3])

Out [22] array([9, 1, 6])
```

To create a multidimensional ndarray, we pass a list specifying the number of values in each dimension. The following example populates a two-dimensional 3×5 array of values between 1 and 10 (exclusive):

```
In [23] np.random.randint(1, 10, [3, 5])

Out [23] array([[2, 9, 8, 8, 7],
               [9, 8, 7, 3, 2],
               [4, 4, 5, 3, 9]])
```

You can provide any number of values inside the list to create ndarrays with more dimensions. A list with three values, for example, will create a three-dimensional array.

C.2.5 The randn function

The `randn` function returns an ndarray with random values from the standard normal distribution. Each sequential argument to the function sets the number of values to store in a dimension. If we pass one argument, the ndarray will have one dimension. The next example creates a 1×3 (1 row by 3 column) array:

```
In [24] np.random.randn(3)

Out [24] array([-1.04474993,  0.46965268, -0.74204863])
```

If we pass two arguments to the `randn` function, the ndarray will have two dimensions, and so on. The next example creates a 2×4 two-dimensional array:

```
In [25] np.random.randn(2, 4)

Out [25] array([[-0.35139565,  1.15677736,  1.90854535,  0.66070779],
               [-0.02940895, -0.86612595,  1.41188378, -1.20965709]])
```

The next example creates a 3-dimensional array with a $2 \times 4 \times 3$ shape. We can think of this shape as being two data sets, each with four rows and three columns:

```
In [26] np.random.randn(2, 4, 3)

Out [26] array([[[ 0.38281118,  0.54459183,  1.49719148],
                 [-0.03987083,  0.42543538,  0.11534431],
                 [-1.38462105,  1.54316814,  1.26342648],
                 [ 0.6256691 ,  0.51487132,  0.40268548]],

                [[[ -0.24774185, -0.64730832,  1.65089833],
                  [ 0.30635744,  0.21157744, -0.5644958 ],
                  [ 0.35393732,  1.80357335,  0.63604068],
                  [ -1.5123853 ,  1.20420021,  0.22183476]]])
```

The `xrand` family of functions is a phenomenal way to generate fake numeric data. We can also create fake data of different types and categories such as names, addresses, or credit cards. For more on that topic, see appendix D.

C.3 The `nan` object

The NumPy library uses a special `nan` object to represent a missing or invalid value. The acronym `nan` is short for *not a number*, a generic catch-all term for missing data. We'll be seeing `nan` frequently throughout the book as we import data sets with missing values into pandas. For now, we can access the `nan` object directly as a top-level attribute on the `np` package:

```
In [27] np.nan
```

```
Out [27] nan
```

A `nan` object is not equal to any value:

```
In [28] np.nan == 5
```

```
Out [28] False
```

A `nan` value is also unequal to another `nan`. From NumPy's perspective, `nan` values are missing or absent. We cannot say with certainty that they are the same, so we assume that they are different.

```
In [29] np.nan == np.nan
```

```
Out [29] False
```

And that's it! Those are the most important details about the NumPy library, which pandas uses underneath its hood.

In your spare time, take a peek at the pandas documentation (https://pandas.pydata.org/docs/user_guide/10min.html). You'll likely see many examples that use NumPy to generate random data.

appendix D

Generating fake data with Faker

Faker is a Python library for generating fake data. It specializes in creating lists of names, phone numbers, street addresses, emails, and the like. In combination with NumPy, which can generate random numeric data, it can quickly create data sets of any size, shape, and type. If you’re looking to practice pandas concepts but can’t find the perfect data set to apply them to, Faker offers a fantastic solution. In this appendix, we’ll walk through everything you need to know to get started with the library.

D.1 *Installing Faker*

First, let’s install the Faker library in our conda environment. In Terminal (macOS) or Anaconda Prompt (Windows), activate the conda environment you’ve set up for this book. When I created an environment for appendix A, I called mine `pandas_in_action`:

```
conda activate pandas_in_action
```

If you’ve forgotten your available Anaconda environments, you can execute `conda info --envs` to see a list of them. When the environment is active, install the Faker library with the `conda install` command:

```
conda install faker
```

When prompted to confirm, enter “Y” for Yes and press Enter. Anaconda will download and install the library. When the process completes, launch Jupyter Notebook and create a new Notebook.

D.2 Getting started with Faker

Let's explore some core features of Faker and then pair it with NumPy to generate a 1,000-row DataFrame. First, we'll import the pandas and NumPy libraries and assign them to their respective aliases (`pd` and `np`). Let's also import the `faker` library:

```
In [1] import pandas as pd  
      import numpy as np  
      import faker
```

The `faker` package exports a `Faker` class (notice the capital F). As a reminder, a *class* is a blueprint for an object—a template for a data structure. `Series` and `DataFrame` are two sample classes from the `pandas` library, and `Faker` is a sample class from the `Faker` library.

Let's create an instance of the `Faker` class with a pair of parentheses and assign the resulting `Faker` object to a `fake` variable:

```
In [2] fake = faker.Faker()
```

A `Faker` object includes many instance methods, each of which returns a random value from a given category. The `name` instance method, for example, returns a string with a person's full name:

```
In [3] fake.name()  
Out [3] 'David Lee'
```

Due to `Faker`'s inherent randomness, the return values will likely vary when you execute the code on your computer. That's totally fine.

We can invoke the complementary `name_male` and `name_female` methods to return full names by gender:

```
In [4] fake.name_male()  
Out [4] 'James Arnold'  
In [5] fake.name_female()  
Out [5] 'Brianna Hall'
```

Use the `first_name` and `last_name` methods to return only a first name or last name:

```
In [6] fake.first_name()  
Out [6] 'Kevin'  
In [7] fake.last_name()  
Out [7] 'Soto'
```

There are also gender-specific `first_name_male` and `first_name_female` methods:

```
In [8] fake.first_name_male()  
Out [8] 'Brian'
```

```
In [9] fake.first_name_female()  
Out [9] 'Susan'
```

As you can see, Faker's syntax is simple but powerful. Here's another example. Suppose that we want to generate some random locations for a data set. The address method returns a string with a complete address, including a street, city, state, and postal code:

```
In [10] fake.address()  
Out [10] '6162 Chase Corner\nEast Ronald, SC 68701'
```

Note that the address is completely fake; it is not an actual location on a map. Faker simply follows conventions on what an address usually looks like.

Notice that Faker separates the street and the remainder of the address with a line break (\n). You can wrap the return value in a print function call to break the address across multiple lines:

```
In [11] print(fake.address())  
Out [11] 602 Jason Ways Apt. 358  
Hoganville, NV 37296
```

We can generate the individual components of an address with methods such as street_address, city, state, and postcode:

```
In [12] fake.street_address()  
Out [12] '58229 Heather Walk'  
In [13] fake.city()  
Out [13] 'North Kristinside'  
In [14] fake.state()  
Out [14] 'Oklahoma'  
In [15] fake.postcode()  
Out [15] '94631'
```

We can generate business-related data with another batch of methods. The following methods return a random company, catchphrase, job title, and URL:

```
In [16] fake.company()  
Out [16] 'Parker, Harris and Sutton'  
In [17] fake.catch_phrase()  
Out [17] 'Switchable systematic task-force'  
In [18] fake.job()  
Out [18] 'Copywriter, advertising'
```

```
In [19] fake.url()
Out [19] 'https://www.gutierrez.com/'
```

Faker also supports email addresses, phone numbers, and credit card numbers:

```
In [20] fake.email()
Out [20] 'sharon13@taylor.com'

In [21] fake.phone_number()
Out [21] '680.402.4787'

In [22] fake.credit_card_number()
Out [22] '4687538791240162'
```

The Faker website (<https://faker.readthedocs.io/en/master>) offers complete documentation for the Faker object's instance methods. The library groups methods into parent categories such as address, automotive, and bank. Figure D.1 shows a sample page from the Faker documentation.

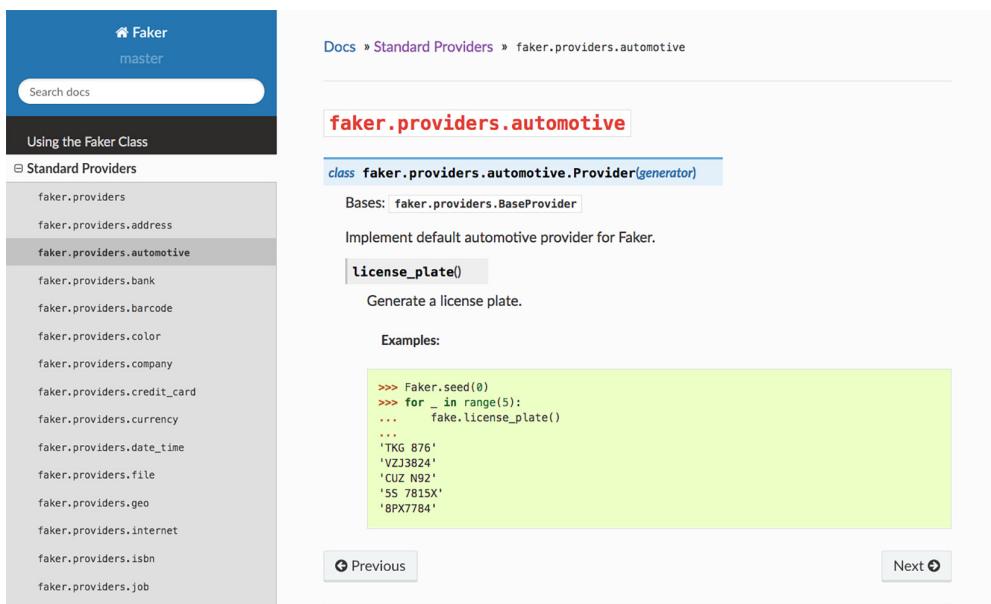


Figure D.1 A sample documentation page on Faker's official website

Take some time to explore Faker's available categories. A little variety can help make the next fake data set you generate a lot more intriguing.

D.3 Populating a DataFrame with fake values

Now that we're comfortable using Faker to generate one fake value, let's use it to populate a whole data set. Our goal is to create a 1,000-row DataFrame with four columns: Name, Company, Email, and Salary.

Here's how we'll tackle the problem: we'll use a `for` loop to iterate 1,000 times, and in each iteration, we'll ask Faker to generate a fake name, company, and email address. We'll also ask NumPy to generate a random number to represent the salary.

We can use Python's `range` function for the iteration. The function accepts an integer argument. It returns an iterable sequence of ascending numbers, starting at 0 and proceeding up to (but not including) the argument. In the next example, we use a `for` loop to iterate over a range of values from 0 (inclusive) to 5 (exclusive):

```
In [23]: for i in range(5):
    print(i)

Out [23]: 0
          1
          2
          3
          4
```

To generate our data set, we'll use `range(1000)` to iterate 1,000 times.

The DataFrame's class constructor accepts various inputs for its `data` parameter, including a list of dictionaries. Pandas maps each dictionary key to a DataFrame column and each value to the row's value for that column. Here's a preview of what we want our input to look like:

```
[{"Name": "Ashley Anderson", "Company": "Johnson Group", "Email": "jessicabrooks@whitaker-crawford.biz", "Salary": 62883}, {"Name": "Katie Lee", "Company": "Ward-Aguirre", "Email": "kennethbowman@fletcher.com", "Salary": 102971} # ... and 998 more dictionaries]
```

You'll notice some logical inconsistencies in the Faker-generated data. The first person's name is Ashley Anderson, for example, but the email is `jessicabrooks@whitaker-crawford.biz`. This inconsistency is due to the randomness of Faker. For the following examples, we're not going to worry about these imperfections. If we want our data set to be more "accurate," however, we can combine Faker with regular Python code to generate whatever values we desire. We can ask Faker for a first name ("Morgan")

and last name ("Robinson"), for example, and then concatenate the two strings to form a more realistic email address ("MorganRobinson@gmail.com"):

```
In [24] first_name = fake.first_name_female()
         last_name = fake.last_name()
         email = first_name + last_name + "@gmail.com"
         email

Out [24] 'MorganRobinson@gmail.com'
```

Back to business. Let's use list comprehension with the `range` function to create a list of 1,000 dictionaries. Within each dictionary, we'll declare the same four keys: "Name", "Company", "Email", and "Salary". For the first three values, we'll invoke the `name`, `company`, and `email` instance methods on our `Faker` object. Remember that Python will invoke these methods on *each* iteration, so the values will differ each time. For the "Salary" value, we'll use NumPy's `randint` function to return a random integer between 50,000 and 200,000. For a more in-depth tutorial on NumPy functions, see appendix C.

```
In [25] data = [
            { "Name": fake.name(),
              "Company": fake.company(),
              "Email": fake.email(),
              "Salary": np.random.randint(50000, 200000)
            }
            for i in range(1000)
        ]
```

Our `data` variable holds a list of 1,000 dictionaries. The last step is passing the list of dictionaries to the `DataFrame` constructor at the top level of pandas:

```
In [26] df = pd.DataFrame(data = data)
         df

Out [26]
```

| | Name | Company | Email | Salary |
|-----|-----------------|---------------------|----------------------|--------|
| 0 | Deborah Lowe | Williams Group | ballbenjamin@gra... | 147540 |
| 1 | Jennifer Black | Johnson Inc | bryannash@carlso... | 135992 |
| 2 | Amy Reese | Mitchell, Hughes... | ajames@hotmail.com | 101703 |
| 3 | Danielle Moore | Porter-Stevens | logan76@ward.com | 133189 |
| 4 | Jennifer Wu | Goodwin Group | vray@boyd-lee.biz | 57486 |
| .. | .. | .. | .. | .. |
| 995 | Joseph Stewart | Rangel, Garcia a... | sbrown@yahoo.com | 123897 |
| 996 | Deborah Curtis | Rodriguez, River... | smithedward@yahoo... | 51908 |
| 997 | Melissa Simmons | Stevenson Ltd | frederick96@hous... | 108791 |
| 998 | Tracie Martinez | Morales-Moreno | caseycurry@lopez... | 181615 |
| 999 | Phillip Andrade | Anderson and Sons | anthony23@glover... | 198586 |

1000 rows × 4 columns

And there you have it—a `DataFrame` with 1,000 rows of random data to practice with. Feel free to explore the `Faker` and NumPy documentation to see what other types of random data you can generate.

appendix E

Regular expressions

A *regular expression* (often abbreviated *RegEx*) is a search pattern for text. It defines a logical sequence of characters that the computer should look for in a string.

Here's a simple example. You've likely used the Find feature in your web browser at some point. In most web browsers, you can access this feature by pressing Ctrl-F in Windows or Command-F in macOS. The browser reveals a dialog box in which we type a sequence of characters. Then the browser searches for those characters on the web page. Figure E.1 shows an example of the browser searching for and finding `romance` in the page's content.

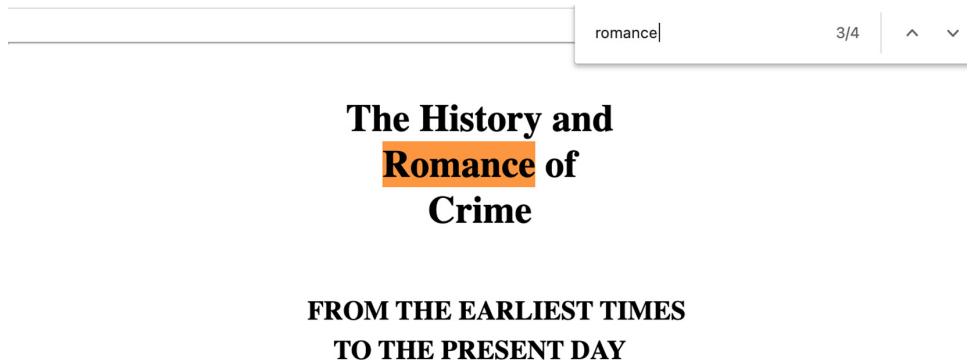


Figure E.1 Searching for the text `romance` by using the Find feature in Google Chrome

Chrome's Find feature is a simple example of RegEx in action. The tool does have its limitations. We can search for characters only in the exact order in which they

appear, for example. We can search for the character sequence "cat", but we cannot declare a condition such as either the letter "c" or "a" or "t". Regular expressions make this kind of dynamic search possible.

A regular expression describes how to look for content in a piece of text. We can search for characters such as letters, digits, or spaces, but we can also use special symbols to declare conditions. Here are a few examples of what we can search for:

- Any two digits in a row
- A sequence of three or more alphabetic characters followed by a space
- The character s, but only at the beginning of a word

In this appendix, we'll explore how regular expressions work in Python and then apply our knowledge to a data set in pandas. Entire textbooks and college courses are dedicated to RegEx, so our hope here is to scratch the surface of this complex field of study. RegEx is easy to get started with and difficult to master.

E.1 *Introduction to Python's re module*

Let's begin by creating a new Jupyter Notebook. We'll import pandas and a special module called `re`. The `re` (regular expressions) module is part of Python's standard library and is built into the language:

```
In [1] import re  
       import pandas as pd
```

The `re` module has a `search` function that looks for a substring in a string. The function accepts two arguments: a search sequence and a string in which to look for it. The next example looks for the string "flower" within the string "field of flowers":

```
In [2] re.search("flower", "field of flowers")  
Out [2] <re.Match object; span=(9, 15), match='flower'>
```

The `search` function returns a `Match` object if Python finds the character sequence in the target string. The `Match` object stores information on what content matched the search pattern and where it exists in the target string. The preceding output communicates that "flower" was found in a span of characters from index positions 9 to 15. The first index is inclusive, and the second index is exclusive. If we count character index positions in "field of flowers", we see that index 9 is the lowercase "f" in "flowers", and index 15 is the "s" in "flowers".

The `search` function returns `None` if the search pattern does not exist in the target string. By default, Jupyter Notebook will not output anything for a `None` value. But we can wrap the `search` invocation in a `print` function to force Jupyter to print the value:

```
In [3] print(re.search("flower", "Barney the Dinosaur"))  
Out [3] None
```

The `search` function returns only the first match in the target string. We can use the `findall` function to find all matches. This function accepts the same two arguments—

a search sequence and a target string—and returns a list of strings that match the search sequence. In the next example, Python finds the search pattern "flower" twice within "Picking flowers in the flower field":

```
In [4] re.findall("flower", "Picking flowers in the flower field")  
Out [4] ['flower', 'flower']
```

Note that the search is case-sensitive.

E.2 Metacharacters

Now let's declare a more complex search pattern using regular expressions. We'll start by assigning a long string to a `sentence` variable. The next code sample breaks the string across multiple lines for readability, but you are welcome to type it in a single line in Jupyter Notebook:

```
In [5] sentence = "I went to the store and bought \"\n      \"5 apples, 4 oranges, and 15 plums.\""  
  
sentence  
  
Out [5] 'I went to the store and bought 5 apples, 4 oranges, and 15 plums.'
```

Inside a regular expression, we can declare *metacharacters*—special symbols that define search patterns. The `\d` metacharacter, for example, instructs Python to match any digit. Let's say we want to identify all digits in our `sentence` string. The next example invokes the `.findall` function with the regular expression "`\d`" as the search pattern:

```
In [6] re.findall("\d", sentence)  
  
Out [6] ['5', '4', '1', '5']
```

The function's return value is a list of the four digits in `sentence` in the order in which they appear:

- the "5" in "5 apples"
- the "4" in "4 oranges"
- the "1" in "15 plums"
- the "5" in "15 plums"

We've learned our first metacharacter! With a simple `\d` symbol, we've created a search pattern that matches any digit in a target string.

Two points are worth mentioning before we move forward:

- When a list contains many elements, Jupyter Notebook likes to print each element on a separate line. This stylistic approach makes the output easier to read but also causes it to take up significant space. To force Jupyter to print the list normally—add line breaks only after a certain threshold of characters has been output—we'll wrap our `.findall` function calls inside Python's built-in `print` function from this point on.

- We'll pass our RegEx arguments to the `.findall` function as raw strings. Python interprets each character in a raw string literally. This parsing option prevents conflicts between regular expressions and escape sequences. Consider the character sequence `\b`. It has a symbolic meaning in a plain Python string and a different meaning in a regular expression. When we use a raw string, we instruct Python to treat `\b` as a literal backslash character followed by a literal `b` character. This syntax guarantees that Python will parse the regular expression's metacharacters correctly.

We declare a raw string with an "`r"` character before the double quotes. Let's rewrite the preceding example with a `print` function call and a raw string:

```
In [7] print(re.findall(r"\d", sentence))
Out [7] ['5', '4', '1', '5']
```

To declare the inverse of an operation, we swap the letter casing of the metacharacter. If `\d` means "match any digit," for example, `\D` means "match any nondigit." Nondigit characters consist of letters, spaces, commas, and symbols. In the next example, we use `\D` to identify all nondigit characters in `sentence`:

```
In [8] print(re.findall(r"\D", sentence))
Out [8] ['I', ' ', 'w', 'e', 'n', 't', ' ', 't', 'o', ' ', 't', 'h', 'e', ' ',
        's', 't', 'o', 'r', 'e', ' ', 'a', 'n', 'd', ' ', 'b', 'o',
        'u', 'g', 'h', 't', ' ', ' ', 'a', 'p', 'p', 'l', 'e', 's', ' ', ' ',
        ' ', 'o', 'r', 'a', 'n', 'g', 'e', 's', ' ', ' ', 'a', 'n',
        'd', ' ', ' ', 'p', 'l', 'u', 'm', 's', '.']
```

Now that you understand the basics of regular expressions, the next step is learning more metacharacters and building complex search queries. Here's another example. The `\w` metacharacter matches any word character, a category that includes letters, digits, and underscores:

```
In [9] print(re.findall(r"\w", sentence))
Out [9] ['I', 'w', 'e', 'n', 't', 'o', 't', 'h', 'e', 's', 't', 'o',
        'r', 'e', 'a', 'n', 'd', 'b', 'o', 'u', 'g', 'h', 't', '5', 'a',
        'p', 'p', 'l', 'e', 's', '4', 'o', 'r', 'a', 'n', 'g', 'e', 's',
        'a', 'n', 'd', 'l', '5', 'p', 'l', 'u', 'm', 's']
```

The inverse `\W` metacharacter matches any nonword character. Nonword characters include spaces, commas, and periods:

```
In [10] print(re.findall(r"\W", sentence))
Out [10] [' ', ',', '.', ' ', ',', '.', ' ', ',', '.', ' ', ',', '.', ' ',
          ' ', ',', '.', '']
```

The `\s` metacharacter searches for any whitespace character:

```
In [11] print(re.findall(r"\s", sentence))
Out [11] [' ', ',', '.', ' ', ',', '.', ' ', ',', '.', ' ', ',', '.', ' ',
          ' ', ',', '.', '']
```

The inverse \S metacharacter searches for any nonwhitespace character:

```
In [12] print(re.findall(r"\S", sentence))

Out [12] ['I', 'w', 'e', 'n', 't', 't', 'o', 't', 'h', 'e', 's', 't', 'o',
'r', 'e', 'a', 'n', 'd', 'b', 'o', 'u', 'g', 'h', 't', '5', 'a',
'p', 'p', 'l', 'e', 's', ',', '4', 'o', 'r', 'a', 'n', 'g', 'e',
's', ',', 'a', 'n', 'd', 'l', '5', 'p', 'l', 'u', 'm', 's', '.']
```

To search for a specific character, declare it literally in the search pattern. The next example searches for all occurrences of the letter "t". This syntax is the same one we used in this appendix's first examples:

```
In [13] print(re.findall(r"t", sentence))

Out [13] ['t', 't', 't', 't', 't']
```

To search for a sequence of characters, write them in order in the search pattern. The next example searches for the letters "to" in the sentence string. Python finds it twice (the "to" word and the "to" in "store"):

```
In [14] print(re.findall(r"to", sentence))

Out [14] ['to', 'to']
```

The \b metacharacter declares a word boundary. A *word boundary* mandates where a character must exist relative to a space. The next example searches for "\bt". The logic translates to "any t character after a word boundary" or, equivalently, "any t character after a space." The pattern matches the "t" characters in "to" and "the":

```
In [15] print(re.findall(r"\bt", sentence))

Out [15] ['t', 't']
```

Let's flip the symbols around. If we use "t\b", we search for "any t character before a word boundary" or, equivalently, "any t character before a space." The "t" characters that Python matches are different. These are the "t" characters at the end of "went" and "bought":

```
In [16] print(re.findall(r"t\b", sentence))

Out [16] ['t', 't']
```

The inverse \B metacharacter declares a nonword boundary. "\Bt", for example, means "any t character that does not come after a word boundary" or, equivalently, "any t character that does not come after a space":

```
In [17] print(re.findall(r"\Bt", sentence))

Out [17] ['t', 't', 't']
```

The preceding example matched the "t" characters in "went", "store", and "bought". Python ignored the "t" characters in "to" and "the" because they appear after a word boundary.

E.3 Advanced search patterns

In review, a *metacharacter* is a symbol that designates a search sequence in a regular expression. Section E.2 explored the \d, \w, \s, and \b metacharacters for digits, word characters, spaces, and word boundaries. Let's learn some new metacharacters and then combine them into a complex search query.

The dot (.) metacharacter matches any character whatsoever:

```
In [18] soda = "coca cola."
      soda

Out [18] 'coca cola.'

In [19] print(re.findall(r".", soda))

Out [19] ['c', 'o', ' ', 'c', 'a', ' ', 'c', 'o', 'l', 'a', '.']
```

At first glance, this metacharacter may not seem to be particularly helpful, but it works wonders when paired with other symbols. The regular expression "c .", for example, searches for the character "c" followed by any character. There are three such matches in our string:

```
In [20] print(re.findall(r"c .", soda))

Out [20] ['co', 'ca', 'co']
```

What if we want to search for a literal dot in a string? In that case, we have to escape it with a backslash in the regular expression. The "\ ." in the next example locates the period at the end of the `soda` string:

```
In [21] print(re.findall(r"\ .", soda))

Out [21] ['.']
```

Earlier, we saw that we could combine characters to search for them in sequence in the target string. Here, we search for the exact sequence of "co":

```
In [22] print(re.findall(r"co", soda))

Out [22] ['co', 'co']
```

What if we want to search for either the character "c" or the character "o"? To do so, we can wrap the characters in a pair of square brackets. The matches will include any occurrence of either "c" or "o" in the target string:

```
In [23] print(re.findall(r"[co]", soda))

Out [23] ['c', 'o', 'c', 'c', 'o']
```

The order of characters in the square brackets does not affect the result:

```
In [24] print(re.findall(r"[oc]", soda))

Out [24] ['c', 'o', 'c', 'c', 'o']
```

Suppose that we want to target any characters between "c" and "l". One option would be to write out the complete sequence of alphabetic characters within the square brackets:

```
In [25] print(re.findall(r"[cdefghijkl]", soda))  
Out [25] ['c', 'c', 'c', 'l']
```

A better solution is to use the dash symbol (-) to declare a range of characters. The following code sample yields the same list as the preceding code:

```
In [26] print(re.findall(r"c-l", soda))  
Out [26] ['c', 'c', 'c', 'l']
```

Next, let's explore how we can target multiple occurrences of characters in a row. Consider the string "bookkeeper":

```
In [27] word = "bookkeeper"  
       word  
Out [27] 'bookkeeper'
```

To search for exactly two "e" characters in a row, we can pair them in the search sequence:

```
In [28] print(re.findall(r"ee", word))  
Out [28] ['ee']
```

We can also search for multiple occurrences of a character with a pair of curly braces. Inside the braces, we declare the number of occurrences to match. In the next example, we search for two "e" characters in a row within "bookkeeper":

```
In [29] print(re.findall(r"e{2}", word))  
Out [29] ['ee']
```

If we search for three "e" characters in a row with "e{3}", the return value will be an empty list because there are no sequences of three consecutive "e" characters in "bookkeeper":

```
In [30] print(re.findall(r"e{3}", word))  
Out [30] []
```

We can also enter two numbers inside the curly braces, separated by a comma. The first value sets the lower bound of occurrences, and the second value sets the upper bound of occurrences. The next example searches for between one and three occurrences of the "e" character in a row. The first match is the sequential "ee" characters in "keeper", and the second match is the final "e" in "keeper":

```
In [31] print(re.findall(r"e{1,3}", word))  
Out [31] ['ee', 'e']
```

Let's walk through this example in more detail. The pattern searches for one to three "e" characters in a row. When Python finds a match, it keeps traversing the string until the search pattern is violated. The regular expression first looks at the letters "bookk" individually. None of these letters fits the search pattern, so Python moves on. Then the pattern locates its first "e". Python cannot mark this match as final yet because the next character may also be an "e", so, it checks the next character. That character is indeed another "e", which fits the original search criteria. Python proceeds to the "p", which does not match the pattern, and declares the match to be "ee" rather than two individual "e" characters. The same logic repeats for the "e" closer to the end of the string.

We're making good progress, but all the previous examples have been mostly theoretical. How can we use RegEx when working with real-world data sets?

Imagine that we are running a customer-support hotline and storing transcriptions of phone calls. We may have a message like this one:

```
In [32] transcription = "I can be reached at 555-123-4567. \"\n"
                           "Look forward to talking to you soon."
```

```
transcription
```

```
Out [32] 'I can be reached at 555-123-4567. Look forward to talking to you
soon.'
```

Let's say we'd like to pull out a phone number from each person's message, but each transcription is unique. We can assume, however, that a phone number has a consistent pattern consisting of

- 1** Three digits
- 2** A dash
- 3** Three digits
- 4** A dash
- 5** Four digits

The beauty of RegEx is that it can identify this search pattern irrespective of the string's contents. The next example declares our most complex regular expression yet. We simply combine metacharacters and symbols to describe the logic above:

- 1** \d{3} searches for exactly three digits.
- 2** - searches for a dash.
- 3** \d{3} searches for exactly three digits.
- 4** - searches for a dash.
- 5** \d{4} searches for exactly four digits.

```
In [33] print(re.findall(r"\d{3}-\d{3}-\d{4}", transcription))
```

```
out [33] ['555-123-4567']
```

Voila!

There's also a convenient `+` metacharacter that indicates "one or more" of the preceding characters or metacharacters. `\d+`, for example, searches for one or more digits in a row. We can use the `+` symbol to simplify the preceding code. The next regular expression holds a different search pattern but returns the same result:

- 1** One or more sequential digits
- 2** A dash
- 3** One or more sequential digits
- 4** A dash
- 5** One or more sequential digits

```
In [34] print(re.findall(r"\d+-\d+-\d+", transcription))
Out [34] ['555-123-4567']
```

With one line of code, we can extract a telephone number from a dynamic piece of text—pretty powerful stuff.

E.4 Regular expressions and pandas

In chapter 6, we introduced the `StringMethods` object for manipulating `Series` of strings. The object is available via the `str` attribute, and many of its methods support RegEx arguments, which significantly expand their power. Let's practice these RegEx concepts on a real data set.

The `ice_cream.csv` data set is a collection of ice cream flavors for four popular brands (Ben & Jerry's, Haagen-Dazs, Breyers, and Talenti). Each row includes a brand, a flavor, and a description:

```
In [35] ice_cream = pd.read_csv("ice_cream.csv")
ice_cream.head()
```

```
Out [35]
```

| | Brand | Flavor | Description |
|---|-----------------|---------------------|------------------------------------|
| 0 | Ben and Jerry's | Salted Caramel Core | Sweet Cream Ice Cream with Blon... |
| 1 | Ben and Jerry's | Netflix & Chilll'd™ | Peanut Butter Ice Cream with Sw... |
| 2 | Ben and Jerry's | Chip Happens | A Cold Mess of Chocolate Ice Cr... |
| 3 | Ben and Jerry's | Cannoli | Mascarpone Ice Cream with Fudge... |
| 4 | Ben and Jerry's | Gimme S'more!™ | Toasted Marshmallow Ice Cream w... |

NOTE `ice_cream` is a modified version of a data set available from Kaggle (<https://www.kaggle.com/tysonpo/ice-cream-dataset>). There are typos and inconsistencies within the data; we have preserved them so that you can see the data irregularities that appear in the real world. I encourage you to consider how you can optimize this data with the techniques you'll learn in this chapter.

I'm curious how many different chocolate treats we can find in the flavors. Our challenge is to find all words that immediately follow the string "Chocolate" within the Description column. We can use the `str.extract` method on a `Series` to accomplish this task. The method accepts a RegEx pattern and returns a `DataFrame` with its matches.

Let's construct our regular expression. We'll begin with a word boundary (\b). Then we'll target the literal text "Chocolate". Next, we'll mandate a single whitespace character (\s). Finally, we'll match one or more word characters in a row (\w+) to capture all alphanumeric letters until Python encounters a space or period. Thus, the final expression is "\bChocolate\s\w+)".

For technical reasons, we have to wrap the regular expression in parentheses when passing it to the `str.extract` method. The method supports an advanced syntax that searches for multiple regular expressions, and the parentheses limit it to one:

```
In [36] ice_cream["Description"].str.extract(r"(\bChocolate\s\w+)").head()
Out [36]
```

| 0 | |
|---|------------------|
| 0 | NaN |
| 1 | NaN |
| 2 | Chocolate Ice |
| 3 | NaN |
| 4 | Chocolate Cookie |

So far, so good. Our Series includes matches such as "Chocolate Ice" at index position 2 and "Chocolate Cookie" at index position 4; it also stores NaN values wherever it could not find the search pattern in the row. Let's invoke the `dropna` method to remove rows with missing values:

```
In [37] (
    ice_cream["Description"]
    .str.extract(r"(\bChocolate\s\w+)")
    .dropna()
    .head()
)
```

```
Out [37]
```

| 0 | |
|----|------------------|
| 2 | Chocolate Ice |
| 4 | Chocolate Cookie |
| 8 | Chocolate Ice |
| 9 | Chocolate Ice |
| 13 | Chocolate Cookie |

We're getting closer.

Next, let's convert the DataFrame to a Series. The `str.extract` method returns a DataFrame by default to support the potential of multiple search patterns. We can use the `squeeze` method to coerce the single-column DataFrame into a Series. You may recall the related `squeeze` parameter from the `read_csv` import function; the `squeeze` method accomplishes the same result:

```
In [38] (
    ice_cream["Description"]
    .str.extract(r"(\bChocolate\s\w+)")
```

```

        .dropna()
        .squeeze()
        .head()
    )

Out [38] 2      Chocolate Ice
         4      Chocolate Cookie
         8      Chocolate Ice
         9      Chocolate Ice
        13     Chocolate Cookie
Name: Chocolate, dtype: object

```

Our method chaining is getting quite lengthy, so let's assign the current Series to a `chocolate_flavors` variable:

```

In [39] chocolate_flavors = (
    ice_cream["Description"]
    .str.extract(r"(\bChocolate\s\w+)")
    .dropna()
    .squeeze()
)

```

We ultimately want to identify what ingredients come after "Chocolate". Let's invoke the `str.split` method to split each string by the occurrence of whitespace. Instead of passing a string with a single space, we'll provide an argument of a regular expression here as well. As a reminder, the "\s" metacharacter looks for a single whitespace:

```

In [40] chocolate_flavors.str.split(r"\s").head()

Out [40] 2      [Chocolate, Ice]
         4      [Chocolate, Cookie]
         8      [Chocolate, Ice]
         9      [Chocolate, Ice]
        13     [Chocolate, Cookie]
Name: 0, dtype: object

```

The `str.get` method retrieves a value at a consistent index position from each list in a Series. In the next example, we retrieve the second element (index position 1) from each list or, equivalently, the word that follows "Chocolate" in the original string:

```

In [41] chocolate_flavors.str.split(r"\s").str.get(1).head()

Out [41] 2      Ice
         4      Cookie
         8      Ice
         9      Ice
        13     Cookie
Name: Chocolate, dtype: object

```

For curiosity's sake, let's invoke the `value_counts` method to see the most frequent words that follow "Chocolate" across all ice cream flavors. Unsurprisingly, "Ice" is the winner. "Cookie" comes in at a distant second:

```
In [42] chocolate_flavors.str.split(r"\s").str.get(1).value_counts()

Out [42]
Ice           11
Cookie        4
Chip          3
Cookies       2
Sandwich      2
Malt          1
Mint          1
Name: Chocolate, dtype: int64
```

Regular expressions offer a sophisticated way of searching for patterns in text. I hope that you've gained greater understanding of the benefits of RegEx and how to apply it to various methods in pandas.

index

Symbols

%matplotlib inline function 320
~ character 126–127

A

advanced search patterns 402–405
agg method 231, 238
aggregate operations 229–232
aggregate, meaning of term 201
Anaconda
 Anaconda distribution 329–330
 environment
 creating new 336–341
 installing xlrd and openpyxl libraries in 301
 installing
 in macOS 330–331
 in Windows 333–335
Anaconda Navigator 341–343
Anaconda Prompt
 commands 335–336
 launching 335
AND condition 124–125
append method 371, 374, 377
apply method 72–78, 232, 237–238, 296–297
arange method 385–386
arguments 357–361
arithmetic operations 43–45
arrays 291
astype method 116–120, 140, 143
attributes 364–365
 DataFrame and Series sharing 84–87
 of GroupBy object 225–229
 on ndarray object 386
 Series object 32–34

B

B metacharacter 401
b metacharacter 401–402
bar graphs 325–327
between method 129, 142, 144
blocks 361, 373
Boolean methods 127–130, 155–157, 351–352
broadcasting Series object 45–47
buckets 221

C

capitalize method 164, 367
cd (change directory) command 333, 336
character replacement 153–155
charts
 line 320–325
 pie 327–328
chop threshold 316–317
class method 167
classes 24, 363–364, 392
closed intervals 70
clusters 221
coding challenges
 DataFrame object 109–112
 dates and times 282–287
 filtering DataFrame 139–143
 GroupBy object 235–237
 importing and exporting 306–309
 MultiIndex DataFrames 194–197
 reshaping and pivoting 214–218
 Series methods 75–77
 Series object 50–52
 text data 162–163
colormaps method 325

- columns
 converting to datetimes 268–269
 extracting values from specific 103–106
 extracting with MultiIndex DataFrames 179–182
 filtering by one or more criteria 15–17
 grouping by multiple 233–234
 maximum width 316
 renaming 106–108
 selecting from DataFrame object 96–99
 selecting multiple columns 97–99
 selecting single column 96–97
 sorting by column index 95
- commands
 Anaconda Prompt 335–336
 Terminal 332–333
- comments 348
- concat function 243–244, 247, 256, 259
- concatenating 239–259
 coding challenge 254–258
 data sets 243–245
 introducing data sets 241–242
 missing values in concatenated
 DataFrames 245–247
- conditions
 between method 128–130
 dealing with null values 132–134
 isin method 127–128
 isnull and notnull methods 130–132
 multiple conditions 124–127
 AND condition 124–125
 inversion with ~ 126–127
 methods for Booleans 127
 OR condition 125–126
 single condition 120–124
- constructors 24
- contains method 155–156, 164
- context blocks 317
- count method 36, 86, 368, 372
- counting values
 in Series 14–15
 with value_counts method 66–72
- cross-sections, MultiIndex DataFrames 188–189
- CSV files 299–301
- cumsum (cumulative sum) method 38
- custom functions 361–362
- custom operations 232–233
-
- D**
- d metacharacter 402
- d+ metacharacter 405
- data
 fake data 391–396
 getting started with Faker 392–394
 installing Faker 391
- populating DataFrame with fake values 395–396
- grouping 18–20
 in 21st century 4
 text data 147–164
 Boolean methods 155–157
 coding challenge 162–163
 letter casing and whitespace 148–151
 regular expressions 163–164
 splitting strings 157–161
 string slicing 151–153
 string slicing and character replacement 153–155
 wide vs. narrow 199–200
- data analysis 7
- data sets
 concatenating 243–245
 creating GroupBy object from 222–225
 importing 9–11
 importing with read_csv function 55–60
 melting 209–213
 optimizing for memory use 114–116
- data types 348–352
 Booleans 351–352
 converting with astype method 116–120
 None object 352
 numbers 348–349
 strings 349–351
- DataFrame 79–112
 coding challenge 109–112
 columns from, selecting 96–99
 selecting multiple columns 97–99
 selecting single column 96–97
 creating
 from dictionary 80–81
 from NumPy ndarray 81–83
 pivot table from DataFrame 200–207
 extracting values from Series 106
 filtering 113–144
 coding challenge 139–143
 by condition 127–134
 converting data types with astype
 method 116–120
 duplicates 134–139
 by multiple conditions 124–127
 optimizing data set for memory use 114–116
 by single condition 120–124
- JSON (JavaScript Object Notation) files
 exporting 298
 loading into 292–298
- manipulating 11–14
 missing values in concatenated 245–247
 populating with fake values 395–396
 renaming columns or rows 106–108
 resetting index 108–109
 rows from, selecting 99–106
 extracting rows by index label 99–101

extracting rows by index position 101–103
 extracting values from specific columns 103–106
 setting new index 95–96
 similarities between Series and 83–90
 importing DataFrame with `read_csv` function 83–84
 shared and exclusive attributes 84–87
 shared methods 87–90
 sorting 90–93
 by index 94–95
 by multiple columns 92–93
 by single column 90–92
 date offsets 275–277
`date()` function 364
 dates and times 260–288
 adding and subtracting durations of time 273–275
 coding challenge 282–287
 converting column or index values to datetimes 268–269
 date offsets 275–277
 storing multiple timestamps in `DatetimeIndex` 266–268
 `timedelta` object 277–282
 `Timestamp` object 261–266
 pandas and datetimes 264–266
 Python and datetimes 261–264
 using `DatetimeProperties` object 269–273
`DatetimeIndex` 266–268
`DatetimeProperties` object 269–273
`day_name` method 271
`day_of_week` function 76–77
 default argument 25, 359
 delimiters 375
 dependencies 329
`describe_option` function 311–312, 318
 dictionaries 30, 80–81, 377–380
`difference` method 382
 dimensions 383–385
`dir` (directory) command 335
`drop` method 163
`drop_duplicates` method 143, 257
`dropna` method 62, 77, 132, 142, 144, 152, 406
`dt` method 271
`dt.day_name` method 271, 284
`duplicated` method 144
`duplicates` 134–139
 `drop_duplicates` method 136–139
 `duplicated` method 134–136

E

elements 368
 empty lists 369
 empty strings 349
`endswith` method 164, 367

environments 329
 equality operators 354–356
 Excel workbooks 301–306
 exporting 305–306
 importing 302–305
 installing `xlrd` and `openpyxl` libraries in Anaconda environment 301
 exceptions 354
`explode` method 214, 219
 exploding list of values 213–214
 exporting 289–309
 coding challenge 306–309
 CSV files 299–301
 Excel workbooks 305–306
 JavaScript Object Notation (JSON) files 290–298
 exporting DataFrame to 298
 loading into DataFrame 292–298
`extend` method 371

F

Faker 391–396
 getting started with 392–394
 installing 391
 populating DataFrame with fake values 395–396
`fillna` method 118, 132, 144
 filtering DataFrame 113–144
 by condition 127–134
 between method 128–130
 dealing with null values 132–134
 `isin` method 127–128
 `isnull` and `notnull` methods 130–132
 by multiple conditions 124–127
 AND condition 124–125
 inversion with `~` 126–127
 methods for Booleans 127
 OR condition 125–126
 by single condition 120–124
 coding challenge 139–143
 column by one or more criteria 15–17
 converting data types with `astype` method 116–120
 duplicates 134–139
 `drop_duplicates` method 136–139
 `duplicated` method 134–136
 optimizing data set for memory use 114–116
`find` method 368
`findall` function 398–400
`first` method 226, 238
 first-class object 72
 flags 332, 337
 flattening 294
`float` function 349, 358
 floating-point number 349
 floor division 353
 foreign keys 240, 259
 forward-fill strategy 39

from_tuples method 167, 169
 functions 10, 357–362
 arguments and return values 357–361
 custom functions 361–362
 invoking on every series value with apply
 method 72–75

G

get method 159–160, 378
 get_group method 222, 228–229, 234, 236
 get_largest_row function 232–233
 get_level_values method 173–174
 get_option function 312, 315
 graphical spreadsheet applications 6–8
 graphs, bar 325–327
 groupby method 220–221, 224, 234–235
 GroupBy object 220–238
 aggregate operations 229–232
 applying custom operation to all groups
 232–233
 attributes and methods of 225–229
 coding challenge 235–237
 creating
 from data set 222–225
 from scratch 221–222
 grouping by multiple columns 233–234
 grouping data 18–20
 groups 221

H

half-open intervals 70
 head method 35–36, 87, 91, 174, 228, 238, 287
 heterogeneous data 85
 heterogeneous lists 369
 hierarchical data 166
 homogeneous data 22, 383
 homogeneous lists 369

I

iloc 186–188
 immutable objects 262, 365
 importing 289–309
 coding challenge 306–309
 CSV files 299–301
 data set with read_csv function 55–60
 data sets 9–11
 Excel workbooks 301–306
 JavaScript Object Notation (JSON) files 290–298
 in keyword 367
 index 350
 converting values to datetimes 268–269
 customizing Series object 26–29
 extracting rows by position 101–103

labels

 extracting rows by 99–101
 merging on 253–254
 sorting DataFrame object by 94–95
 sorting with sort_index method 62–64
 stacking and unstacking levels 207–209

index method 368

index position 12

inequality operators 354–356

info method 115, 117, 119, 172, 283–284

inner joins 249–250

inplace parameter 65–66

insert method 371, 377

installing 329–346

 Anaconda distribution 329–330

 Anaconda environment

 creating new 336–341

 xlrd and openpyxl libraries in 301

 Anaconda Navigator 341–343

 Faker 391

 Jupyter Notebook 343–346

 macOS setup process 330–333

 Anaconda 330–331

 common Terminal commands 332–333

 launching Terminal 331–332

 matplotlib 320

 Windows setup process 333–336

 Anaconda 333–335

 common Anaconda Prompt commands

 335–336

 launching Anaconda Prompt 335

 instances 24, 363

 instantiation 363

 int function 358

 intersection method 381

 inversion with 126–127

 invoking functions 357

 isin method 127–128, 142

 isnull methods 130–132

 isspace method 366

 iterations

 dictionary 380

 list 373–374

J

join method 376

joining 239–259

 coding challenge 254–258

 inner joins 249–250

 introducing data sets 241–242

 left joins 247–248

 outer joins 251–253

joins 247

JSON (JavaScript Object Notation) files 290–298

 exporting DataFrame to 298

 loading into DataFrame 292–298

json_normalize function 294–297, 307, 309
Jupyter Notebook 343–346

K

keyword arguments 360

L

labels 22
last method 226, 238
last_name method 392
left joins 247–248
len function 72, 235, 357–358, 369, 374
letter casing 148–151
libraries 3, 329
line charts 320–325
linters 291
list function 31
lists 368–376
 converting string to 375–376
 list comprehension 374–375
 list iteration 373–374
literals 363
loc 182–186
local variables 362
long data set 199
lower method 150, 155–156, 164, 366–367
lstrip (left strip) method 149, 367

M

macOS 330–333
 installing Anaconda in 330–331
 Terminal
 commands 332–333
 launching 331–332
mathematical operations 36–47, 352–354
 arithmetic operations 43–45
 broadcasting 45–47
 statistical operations 36–43
matplotlib 320
max method 69, 72, 88, 232, 236, 281
maximum column width 316
mean method 222–223, 230, 236, 271, 281, 287
melt method 211–212, 217–219
melting 211
merge method 248–249, 251–253, 256, 258–259
merging 239–259
 coding challenge 254–258
 introducing data sets 241–242
 on index labels 253–254
metacharacters 399–401
method chaining 69, 367
methods 34, 364–365
 DataFrame and Series sharing 87–90

for Booleans 127
of GroupBy object 225–229
microseconds 283
min method 69, 72, 88–89, 231, 237, 281
missing values
 creating Series object with 29–30
 in concatenated DataFrames 245–247
modules 261, 362–363
modulo operator 353
MultiIndex DataFrames 165–197
 coding challenge 194–197
 cross-sections 188–189
 manipulating 189–194
 resetting index 189–193
 setting index 193–194
 MultiIndex object 166–170
 selecting with 179–188
 extracting one or more columns 179–182
 extracting one or more rows with iloc 186–188
 extracting one or more rows with loc 182–186
 sorting 175–179
MultiIndex object 166–170
munging 147
mutable object 365

N

nan object 390
narrow data 199–200
ndarray object 385–390
 attributes on 386
 generating numeric range with arange
 method 385–386
 randint function 388–389
 randn function 389–390
 reshape method 386–388
nlargest method 64–65, 89, 110, 232
None object 352
normalizing 294
not a number 29, 390
notnull method 130–132, 144
nsmallest method 64–65, 89, 91
nth method 226–227, 238
null values 132–134
numbers 348–349
NumPy 383–390
 dimensions 383–385
 nan object 390
 ndarray object 385–390
 attributes on 386
 creating DataFrame object from 81–83
 generating numeric range with arange
 method 385–386
 randint function 388–389
 randn function 389–390
 reshape method 386–388
nunique method 67, 88, 118, 140, 174, 194

O

objects 363–364
 OOP (object-oriented programming) 347
 open intervals 70
 openpyxl libraries 301
 operands 352
 operators 352–356
 equality and inequality 354–356
 mathematical 352–354
 option_context function 317–318
 OR condition 125–126
 order 22
 outer joins 251–253
 overwriting 65–66

P

packages 3, 320, 329
 pandas 3–21
 competitors vs. 8–9
 configuring 310–318
 chop threshold 316–317
 maximum column width 316
 option context 317–318
 options 311–315
 precision 315–316
 data in 21st century 4
 datetimes and 264–266
 graphical spreadsheet applications vs. 6–8
 regular expressions and 405–408
 tour of 9–20
 counting values in Series 14–15
 filtering column by one or more criteria 15–17
 grouping data 18–20
 importing data set 9–11
 manipulating DataFrame 11–14
 parameters 25, 359, 361
 pct_change (percent change) method 39
 pd.DataFrame() function 80
 pd.Series() function 25
 pie charts 327–328
 pivot_table method 201–205, 212, 215–216, 218
 pivoting 198–219
 coding challenge 214–218
 creating pivot table from DataFrame 200–207
 additional options for pivot tables 205–207
 pivot_table method 201–205
 exploding list of values 213–214
 melting data set 209–213
 stacking and unstacking index levels 207–209
 wide vs. narrow data 199–200
 plot method 321–323, 325–328
 pop method 372, 377, 379
 precision 315–316
 primary keys 240, 253, 259
 print function 358–360, 378, 393, 398–400

product method 37
 pwd (print working directory) command 332–333
 PyPi (Python Package Index) 347
 Python 347–382
 attributes and methods 364–365
 classes and objects 363–364
 creating Series object from 30–32
 data types 348–352
 Booleans 351–352
 None object 352
 numbers 348–349
 strings 349–351
 datetimes and 261–264
 dictionaries 377–380
 functions 357–362
 arguments and return values 357–361
 custom functions 361–362
 lists 368–376
 converting string to 375–376
 list comprehension 374–375
 list iteration 373–374
 modules 362–363
 operators 352–356
 equality and inequality 354–356
 mathematical 352–354
 passing Series object to functions 48–49
 re module 398–399
 sets 380–382
 string methods 365–368
 tuples 376–377
 variables 356–357
 Pythonic way 375

Q

quotient 353

R

randint function 31, 81, 388–389, 396
 randn function 389–390
 range function 34
 RDBMS (relational database management systems) 239
 read_csv function 10, 54, 77, 79, 96, 109–110, 114, 132, 140, 157, 170–171, 189, 201, 242, 255, 268, 293, 299, 302, 309
 importing data sets with 55–60
 importing DataFrame with 83–84
 read_excel function 302–303, 309
 read_json function 293, 309
 RegEx (regular expressions) 163–164, 312, 397–408
 advanced search patterns 402–405
 metacharacters 399–401
 pandas and 405–408
 Python’s re module 398–399

relational databases 8
remove method 372
rename method 107, 112
renaming columns or rows 106–108
reorder_levels method 190
replace method 152, 155, 164, 366
reset_index method 108, 111–112, 190–192, 197
reset_option function 315, 318
resetting index 108–109, 189–193
reshape method 386–388
reshaping 198–219
 coding challenge 214–218
 creating pivot table from DataFrame 200–207
 additional options for pivot tables 205–207
 pivot_table method 201–205
 exploding list of values 213–214
 melting data set 209–213
 stacking and unstacking index levels 207–209
 wide vs. narrow data 199–200
return values 357–361
round function 68, 73
rows 171
 extracting
 with iloc 186–188
 with loc 182–186
 renaming 106–108
 retrieving first and last 34–36
 selecting from DataFrame object 99–106
 extracting rows by index label 99–101
 extracting rows by index position 101–103
 extracting values from specific columns
 103–106
 sorting by index 94
rstrip (right strip) method 366

S

S metacharacter 401
s metacharacter 400, 402, 407
sample method 88
save method 306, 309
search function 398
search patterns, advanced 402–405
select_dtypes method 98
Series object 22–78
 attributes 32–34
 classes and instances 24
 coding challenge 50–52, 75–77
 counting values in 14–15, 66–72
 creating
 from Python objects 30–32
 with missing values 29–30
 customizing index 26–29
 extracting values from 106
 importing data set with read_csv function 55–60
 invoking function with apply method 72–75
 mathematical operations 36–47

arithmetic operations 43–45
broadcasting 45–47
statistical operations 36–43
overwriting with inplace parameter 65–66
passing to Python’s built-in functions 48–49
populating with values 24–26
retrieving first and last rows 34–36
similarities between DataFrame object and
83–90
importing DataFrame with read_csv
 function 83–84
shared and exclusive attributes 84–87
shared methods 87–90
sorting 60–65
 by index with sort_index method 62–64
 by values with sort_values method 60–62
 retrieving with nsmallest and nlargest
 methods 64–65
set function 381
set_index method 95, 108, 110, 177, 193, 197
set_option function 312, 314, 318
setdefault method 296–297
sets 380–382
setting index 95–96, 193–194
size method 224, 233, 236
slice method 153–155
slicing 350
sort_index method 62–64, 78, 94–95, 175–176,
197, 267
sort_values method 60–62, 65–66, 78, 90–93,
110–112, 175, 281–282, 287
sorting 60–65
 by index with sort_index method 62–64
 by values with sort_values method 60–62
 DataFrame object 90–93
 by index 94–95
 by multiple columns 92–93
 by single column 90–92
 MultiIndex DataFrames 175–179
 nsmallest and nlargest methods 64–65
split method 158–159, 161–162, 164, 375–376
splitting strings 157–161
SQL (Structured Query Language) 8
squeeze method 406
stack method 208, 217, 219
stacking index levels 207–209
standard library 261, 362
startswith method 164, 367
statistical operations 36–43
str function 155, 358
str.capitalize method 151
str.endswith method 157
str.extract method 405–406
str.get method 159, 407
str.len method 158
str.replace method 155
str.slice method 154

str.split method 158, 160, 213, 407
 str.startswith method 156
 str.strip method 150
 str.title method 151
 str.upper method 151
 strftime method 75, 77
 strings 349–351
 methods 365–368
 slicing 151–155
 strip method 149, 162, 164, 367, 375
 subtracting duration of time 273–275
 sum method 37, 86–87, 229–230
 SUMIF function 6
 swapcase method 366
 symmetric_difference method 382

T

tail method 35–36, 228, 238
 tall data set 199
 Terminal
 commands 332–333
 launching 331–332
 text data 147–164
 Boolean methods 155–157
 coding challenge 162–163
 letter casing and whitespace 148–151
 regular expressions 163–164
 splitting strings 157–161
 string slicing 151–153
 string slicing and character replacement
 153–155
 time-series graph 321
 timedelta object 277–282
 times and dates 260–288
 adding and subtracting durations of time
 273–275
 coding challenge 282–287
 converting column or index values to
 datetimes 268–269
 date offsets 275–277
 storing multiple timestamps in
 DatetimeIndex 266–268
 timedelta object 277–282
 Timestamp object 261–266
 pandas and datetimes 264–266
 Python and datetimes 261–264
 using DatetimeProperties object 269–273
 title method 151, 164, 367
 to_csv method 299–300
 to_datetime function 269, 279, 283–284, 288
 to_excel method 305–306, 308–309
 to_json method 298
 to_timedelta function 278, 285
 transpose method 81

tuple function 30, 376
 tuples 376–377
 type function 32, 294, 363

U

union method 382
 unique method 152
 unstack method 208–209, 219
 unstacking index levels 207–209
 upper method 155, 164, 365, 371

V

value_counts method 66–72, 78, 85, 110, 284, 286,
 325, 327
 values
 counting with value_counts method 66–72
 creating Series object with missing 29–30
 exploding list of 213–214
 populating Series object with 24–26
 sorting with sort_values method 60–62
 values method 380
 variables 11, 199, 356–357, 365
 VBA (Visual Basic for Applications) 7
 visualization 319–328
 bar graphs 325–327
 installing matplotlib 320
 line charts 320–325
 pie charts 327–328
 VLOOKUP function 6

W

W metacharacter 400
 w metacharacter 400
 weekday method 364–365
 whitespace 148–151
 wide data 199–200
 Windows 333–336
 Anaconda Prompt
 commands 335–336
 launching 335
 installing Anaconda in 333–335
 word boundaries 401
 wrangling 147

X

xlrd libraries 301
 xs method 188–189, 196

Pandas in Action

Boris Paskhaver

Data analysis with Python doesn't have to be hard. If you can use a spreadsheet, you can learn pandas! While its grid-style layouts may remind you of Excel, pandas is far more flexible and powerful. This Python library quickly performs operations on millions of rows, and it interfaces easily with other tools in the Python data ecosystem. It's a perfect way to up your data game.

Pandas in Action introduces Python-based data analysis using the amazing pandas library. You'll learn to automate repetitive operations and gain deeper insights into your data that would be impractical—or impossible—in Excel. Each chapter is a self-contained tutorial. Realistic downloadable datasets help you learn from the kind of messy data you'll find in the real world.

What's Inside

- Organize, group, merge, split, and join datasets
- Find trends in text-based and time-based data
- Sort, filter, pivot, optimize, and draw conclusions
- Apply aggregate operations

For readers experienced with spreadsheets and basic Python programming.

Boris Paskhaver is a software engineer, Agile consultant, and online educator. His programming courses have been taken by 300,000 students across 190 countries.

Register this print book to get free access to all ebook formats.

Visit <https://www.manning.com/freebook>

“Of all the introductory pandas books I've read—and I did read a few—this is the best, by a mile.”

—Erico Lendzian, idibu.com

“This approachable guide will get you up and running quickly with all the basics you need to analyze your data.”

—Jonathan Sharley
SiriusXM Media

“Understanding and putting in practice the concepts of this book will help you increase productivity and make you look like a pro.”

—Jose Apablaza
Steadfast Networks

“Teaches both novice and expert Python users the essential concepts required for data analysis and data science.”

—Ben McNamara, DataGeek



ISBN: 978-1-61729-743-4



MANNING

\$59.99 / Can \$79.99 [INCLUDING eBOOK]