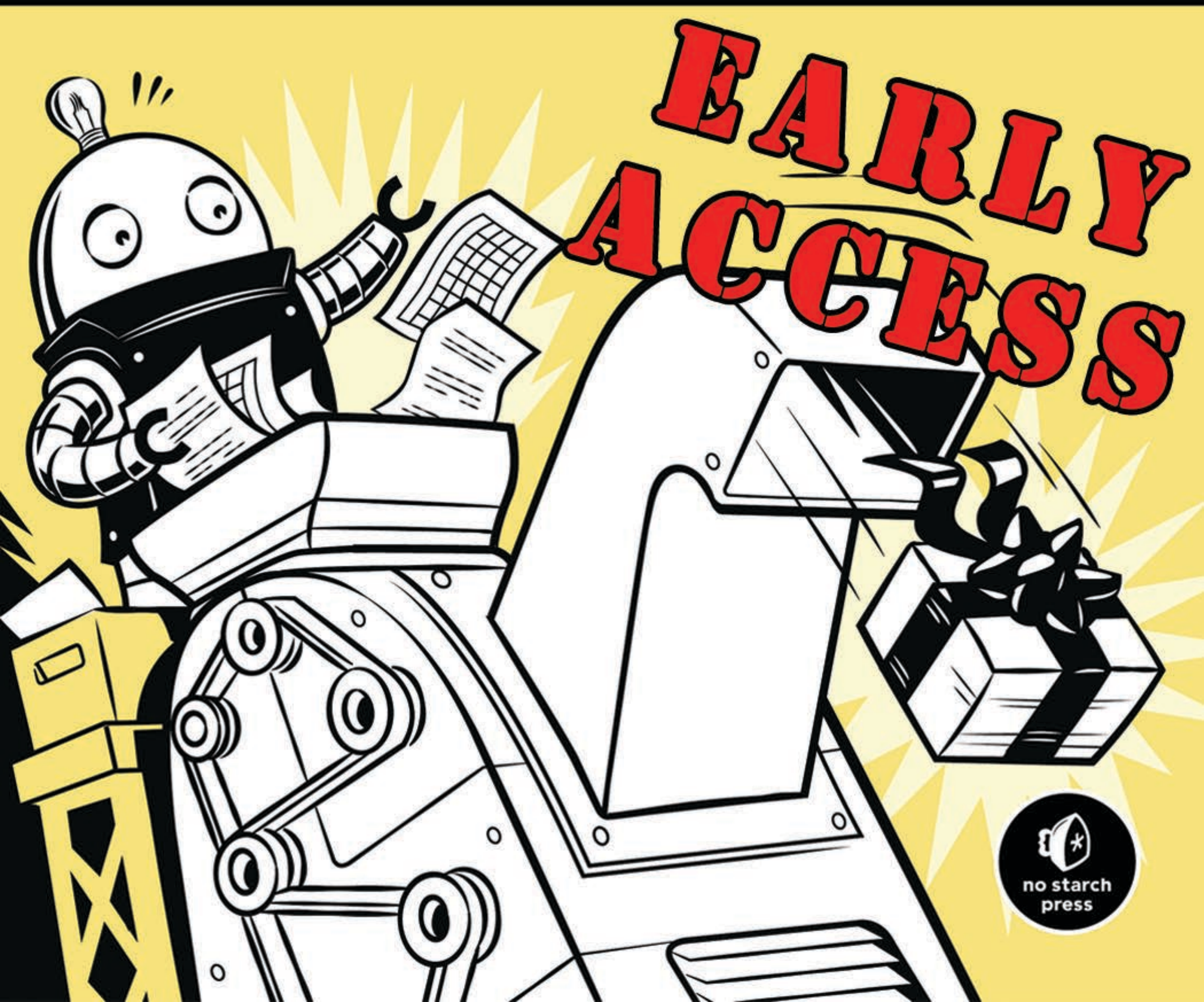
PRACTICAL SQL

A BEGINNER'S GUIDE TO STORYTELLING WITH DATA

ANTHONY DEBARROS



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We'll email you as new chapters become available. In the meantime, enjoy!

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BRIEF CONTENTS

INTRODUCTION

Shortly after joining the staff of *USA TODAY* I received a data set I would analyze almost every week for the next decade. It was the weekly Best-Selling Books list, which ranked the nation's top-selling books based on confidential sales data. The list not only produced an endless stream of story ideas to pitch, but it also captured the zeitgeist of America in a most singular way.

For example, did you know that cookbooks sell a bit more during the week of Mother's Day or that Oprah Winfrey turned many obscure writers into number one best-selling authors just by having them on her show? Week after week, the book list editor and I pored over the sales figures and book genres, ranking the data in search of the next headline. Rarely did we come up empty: we chronicled everything from the rocket-rise of the blockbuster *Harry Potter* series to the fact that *Oh, the Places You'll Go!* by Dr. Seuss has become a perennial gift for new graduates.

My technical companion during this time was the database programming language *SQL* (for *Structured Query Language*). Early on, I convinced *USA TODAY*'s IT department to grant me access to the SQL-based database system that powered our book list application. Using SQL, I was able to unlock the stories hidden in the database, which contained titles, authors, genres, and various codes that defined the publishing world. Uncovering important stories in a database is exactly what you'll learn to do using this book.

What Is SQL?

SQL is a widely used programming language that allows you to define and query databases. Whether you're a marketing analyst, a journalist, or a researcher mapping neurons in the brain of a fruit fly, you'll benefit from using SQL to manage database objects as well as create, modify, explore, and summarize data.

Because SQL is a mature language that has been around for decades, it's deeply ingrained in many modern systems. A pair of IBM researchers first outlined the syntax for SQL (then called SEQUEL) in a 1974 paper, building on the theoretical work of the British computer scientist Edgar F. Codd. In 1979, a precursor to the database company Oracle (then called Relational Software) became the first to use the language in a commercial product. Today, it continues to rank as one of the most-used computer languages in the world, and that's unlikely to change soon.

SQL comes in several variants, which are generally tied to specific database systems. The American National Standards Institute (ANSI) and International Organization for Standardization (ISO), which set standards for products and technologies, provide standards for the language and shepherd revisions to it. The good news is that the variants don't stray far from the standard, so once you learn the SQL conventions for one database, you can transfer that knowledge to other systems.

Why Use SQL?

So why should you use SQL? After all, SQL is not usually the first tool people choose when they're learning to analyze data. In fact, many people start with Microsoft Excel spreadsheets and their assortment of analytic functions. After working with Excel, they might graduate to Access, the database system built into Microsoft Office, which has a graphical query interface that makes it easy to get work done, making SQL skills optional.

But as you might know, Excel and Access have their limits. Excel currently allows 1,048,576 rows maximum per worksheet, and Access limits database size to two gigabytes and limits columns to 255 per table. It's not uncommon for data sets to surpass those limits, particularly when you're working with data dumped from government systems. The last obstacle you want to discover while facing a deadline is that your database system doesn't have the capacity to get the job done.

Using a robust SQL database system allows you to work with terabytes of data, multiple related tables, and thousands of columns. It gives you improved programmatic control over the structure of your data, leading to efficiency, speed, and—most important—accuracy.

SQL is also an excellent adjunct to programming languages used in the data sciences, such as R and Python. If you use either language, you can connect to SQL databases and, in some cases, even incorporate SQL syntax directly into the language. For people with no background in programming languages, SQL often serves as an easy-to-understand introduction into concepts related to data structures and programming logic.

Additionally, knowing SQL can help you beyond data analysis. If you delve into building online applications, you'll find that databases provide the backend power for many common web frameworks, interactive maps, and content management systems. When you need to dig beneath the surface of these applications, SQL's capability to manipulate data and databases will come in very handy.

About This Book

Practical SQL is for people who encounter data in their everyday lives and want to learn how to analyze and transform it. To this end, I discuss real-world data and scenarios, such as US Census demographics, crime statistics, and data about taxi rides in New York City. Along with information about databases and code, you'll also learn tips on how to analyze and acquire data as well as other valuable tips I've accumulated throughout my career. I won't focus on setting up servers or other tasks typically handled by a database administrator, but the SQL and PostgreSQL fundamentals you learn in this book will serve you well if you intend to go that route.

I've designed the exercises for beginner SQL coders but will assume that you know your way around your computer, including how to install programs, navigate your hard drive, and download files from the internet. Although many chapters in this book can stand alone, you should work through the book sequentially to build on the fundamentals. Some data sets used in early chapters reappear later in the book, so following the book in order will help you stay on track.

Practical SQL starts with the basics of databases, queries, tables, and data that are common to SQL across many database systems. Chapters 13 to 17 cover topics more specific to PostgreSQL, such as full text search and GIS. The following table of contents provides more detail about the topics discussed in each chapter:

Chapter 1: Creating Your First Database and Table

Chapter 2: Beginning Data Exploration with SELECT

Chapter 3: Understanding Data Types

Chapter 4: Importing and Exporting Data

Chapter 5: Basic Math and Stats with SQL

Chapter 6: Joining Tables in a Relational Database

Each chapter ends with a "Try It Yourself" section that contains exercises to help you reinforce the topics you learned. At the end of the book, Appendix A presents a framework for identifying trends in data and presenting them effectively to your audience. Appendix B lists some helpful PostgreSQL resources and readings.

Using the Book's Code Examples

Each chapter includes code examples and most use data sets I've already compiled. All the code and sample data in the book are available to download at *https://www.nostarch.com/practicalSQL/*. Click the **Download the code from GitHub** link to go to the GitHub repository that holds this material. At GitHub, you should see a "Clone or Download" button that gives you the option to download a ZIP file with all the materials. Save the file to your computer in a location where you can easily find it, such as your desktop.

Inside the ZIP file is a folder for each chapter. Each folder contains a file named *Chapter_XX* (*XX* is the chapter number) that ends with a *.sql* extension. You can open those files with a text editor or with the PostgreSQL administrative tool you'll install. You can copy and paste code when the book instructs you to run it. Note that in the book, several code examples are truncated to save space, but you'll need the full listing from the *.sql* file to complete the exercise. You'll know an example is truncated when you see `--snip--` inside the listing.

Also in the *.sql* files, you'll see lines that begin with two hyphens (`--`) and a space. These are comments that provide the code's listing number and additional context, but they're not part of the code. These comments also note when the file has additional examples that aren't in the book.

NOTE *After downloading data, Windows users might need to provide permission for the database to read files. To do so, right-click the folder containing the code and data,* *select Properties, and click the Security tab. Click* ***Edit****, then* ***Add****. Type the name Everyone into the object names box and click* ***OK****. Highlight Everyone in the user list, select all boxes under Allow, and then click* ***Apply*** *and* ***OK****.*

Using PostgreSQL

In this book, I'll teach you SQL using the open source *PostgreSQL* database system. PostgreSQL, or simply Postgres, is a robust database system that can handle very large amounts of data. Here are some reasons PostgreSQL is a great choice to use with this book:

- It's free.
- It's available for Windows, macOS, and Linux operating systems.
- Its SQL implementation closely follows ANSI standards.
- It's widely used for analytics and data mining, so finding help online from peers is easy.
- Its geospatial extension, PostGIS, lets you analyze geometric data and perform mapping functions.
- It's available in several variants, such as Amazon Redshift and Citus, which focus on processing huge data sets.
- It's a common choice for web applications, including those powered by the popular web frameworks Django and Ruby on Rails.

Of course, you can also use another database system, such as Microsoft SQL Server or MySQL: many code examples in this book translate easily to either SQL implementation. However, some examples, especially later in the book, do not, and you'll need to search online for equivalent solutions. Where appropriate, I'll note whether an example code follows the ANSI SQL standard and may be portable to other systems or whether it's PostgreSQL specific.

Installing PostgreSQL

You'll start by installing the PostgreSQL database and the graphical administrative tool *pgAdmin*, which is software that makes it easy to manage your database, import and export data, and write queries.

One great benefit of working with PostgreSQL is that regardless of whether you work on Windows, macOS, or Linux, the open source community has made it easy to get PostgreSQL up and running. The following sections outline installation for all three operating systems as of this writing, but options might change as new versions are released. Check the documentation noted in each section as well as the GitHub repository with the book's resources: I'll maintain the files with updates and answers to frequently asked questions.

NOTE *Always install the latest available version of PostgreSQL for your operating system to ensure that it's up to date on security patches and new features. For this book, I'll assume you're using version 10.0 or later.*

Windows Installation

For Windows, I recommend using the installer provided by the company EnterpriseDB, which offers support and services for PostgreSQL users. EnterpriseDB's package bundles PostgreSQL with pgAdmin and the company's own Stack Builder, which also installs the spatial database extension PostGIS and programming language support, among other tools. To get the software, visit *https://www.enterprisedb.com/* and create a free account. Then go to the downloads page at *https://www.enterprisedb.com/software-downloads-postgres/*.

Select the latest available 64-bit Windows version of EDB Postgres Standard unless you're using an older PC with 32-bit Windows. After you download the installer, follow these steps:

1. Right-click the installer and select **Run as administrator**. Answer **Yes** to the question about allowing the program to make changes to your computer. The program will perform a setup task and then present an initial welcome screen. Click through it.
2. Choose your installation directory, accepting the default.
3. On the Select Components screen, select the boxes to install PostgreSQL Server, the pgAdmin tool, Stack Builder, and Command Line Tools.
4. Choose the location to store data. You can choose the default, which is in a "data" subdirectory in the PostgreSQL directory.
5. Choose a password. PostgreSQL is robust with security and permissions. This password is for the initial database superuser account, which is called `postgres`.
6. Select a port number where the server will listen. Unless you have another database or application using it, the default of `5432` should be fine. If you have another version of PostgreSQL already installed or some other application is using that default, the value might be `5433` or another number, which is also okay.
7. Select your locale. Using the default is fine. Then click through the summary screen to begin the installation, which will take several minutes.
8. When the installation is done, you'll be asked whether you want to launch EnterpriseDB's Stack Builder to obtain additional packages. Select the box and click **Finish**.
9. When Stack Builder launches, choose the PostgreSQL installation on the drop-down menu and click **Next**. A list of additional applications should download.

10. Expand the **Spatial Extensions** menu and select either the 32-bit or 64-bit version of PostGIS Bundle for the version of Postgres you installed. Also, expand the **Add-ons, tools and utilities** menu and select EDB Language Pack, which installs support for programming languages including Python. Click through several times: you'll need to wait while the installer downloads the additional components.
11. When installation files have been downloaded, click **Next** to install both components. For PostGIS, you'll need to agree to the license terms; click through until you're asked to Choose Components. Make sure PostGIS and Create spatial database are selected. Click **Next**, accept the default database location, and click **Next** again.
12. Enter your database password when prompted and continue through the prompts to finish installing PostGIS.
13. Answer **Yes** when asked to register GDAL. Also, answer **Yes** to the questions about setting POSTGIS_ENABLED_DRIVERS and enabling the POSTGIS_ENABLE_OUTDB_RASTERS environment variable.

When finished, a PostgreSQL folder that contains shortcuts and links to documentation should be on your Windows Start menu.

If you experience any hiccups installing PostgreSQL, refer to the "Troubleshooting" section of the EDB guide at *https://www.enterprisedb.com/docs/en/10.0/pg/toc.html*. If you're unable to install PostGIS via Stack Builder, try downloading a separate installer from the PostGIS site at *http://postgis.net/windows_downloads/* and consult the guides at *http://postgis.net/documentation/*.

Mac Installation

For Mac users, I recommend obtaining *Postgres.app*, an open source macOS application that includes PostgreSQL as well as the PostGIS extension and a few other goodies:

1. Visit *http://postgresapp.com/* and download the app's Disk Image file that ends in *.dmg*.
2. Double-click the *.dmg* file to open it, and then drag and drop the app icon into your Mac's */Applications* folder.
3. Double-click the app icon. When Postgres.app opens, click **Initialize** to create and start a PostgreSQL database.

A small elephant icon in your menu bar indicates that you now have a database running. To use included PostgreSQL command line tools, you'll need to open your Mac's Terminal application and run the following code at the prompt (you can copy the code from the Postgres.app site at *https://postgresapp.com/documentation/install.html*):

```
sudo mkdir -p /etc/paths.d &&
echo /Applications/Postgres.app/Contents/Versions/latest/bin | sudo tee /etc/paths.d/
postgresapp
```

Because Postgres.app doesn't include pgAdmin, you'll need to follow these steps to download and run pgAdmin:

1. Visit the pgAdmin site's page for Mac downloads at *https://www.pgadmin.org/download/pgadmin-4-macos/*.
2. Select the latest version and download the installer (look for a Disk Image file that ends in *.dmg*).
3. Double-click the *.dmg* file, click through the prompt to accept the terms, and then drag pgAdmin's elephant app icon into your */Applications* folder.
4. Double-click the app icon to launch pgAdmin.

NOTE *On a Mac, when you launch pgAdmin the first time, a dialog might appear that displays, "pgAdmin4.app can't be opened because it is from an unidentified developer." Right-click the icon and select* ***Open****. The next dialog should give you the option to open the app; going forward, your Mac will remember you've granted this permission.*

Mac installation is relatively simple, but if you encounter any issues, review the documentation for Postgres.app at *https://postgresapp.com/documentation/* and for pgAdmin at *https://www.pgadmin.org/docs/*.

Linux Installation

If you're a Linux user, installing PostgreSQL becomes simultaneously easy and difficult, which in my experience is very much the way it is in the Linux universe. Most popular Linux distributions—including Ubuntu, Debian, and CentOS—bundle PostgreSQL in their standard package. However, some distributions stay on top of updates more so than others. The best path is to consult your distribution's documentation for the best way to install PostgreSQL if it's not already included or if you want to upgrade to a more recent version.

Alternatively, the PostgreSQL project maintains complete up-to-date package repositories for Red Hat variants, Debian, and Ubuntu. Visit *https://yum.postgresql.org/* and *https://wiki.postgresql.org/wiki/Apt/* for details. The packages you'll want to install include the client and server for PostgreSQL, pgAdmin (if available), PostGIS, and PL/Python. The exact names of these packages will vary according to your Linux distribution. You might also need to manually start the PostgreSQL database server.

On the other hand, pgAdmin is rarely part of Linux distributions. To install it, refer to the pgAdmin site at *https://www.pgadmin.org/download/* for the latest instructions and to see whether your platform is supported. If you're feeling adventurous, you can find instructions on building the app from source code at *https://www.pgadmin.org/download/pgadmin-4-source-code/*.

Working with pgAdmin

Before you can start writing code, you'll need to become familiar with pgAdmin, which is the administration and management tool for PostgreSQL. It's also free, but don't underestimate its performance. In fact, pgAdmin is a full-featured tool, similar to tools for purchase, such as Microsoft's SQL Server Management Studio, in its capability to let you control multiple aspects of server operations. It also includes a graphical interface for configuring and administrating your PostgreSQL server and databases, and—most appropriately for this book—offers a SQL query tool for writing, testing, and saving queries.

If you're using Windows, pgAdmin should come with the PostgreSQL package you downloaded from EnterpriseDB. On the Start menu, select **PostgreSQL ▸ pgAdmin 4** (the version number of Postgres should also appear in the menu). If you're using a Mac and have installed pgAdmin separately, click the pgAdmin icon in your */Applications* folder, making sure you've also launched Postgres.app.

When you open pgAdmin, it should look similar to Figure 0-1:

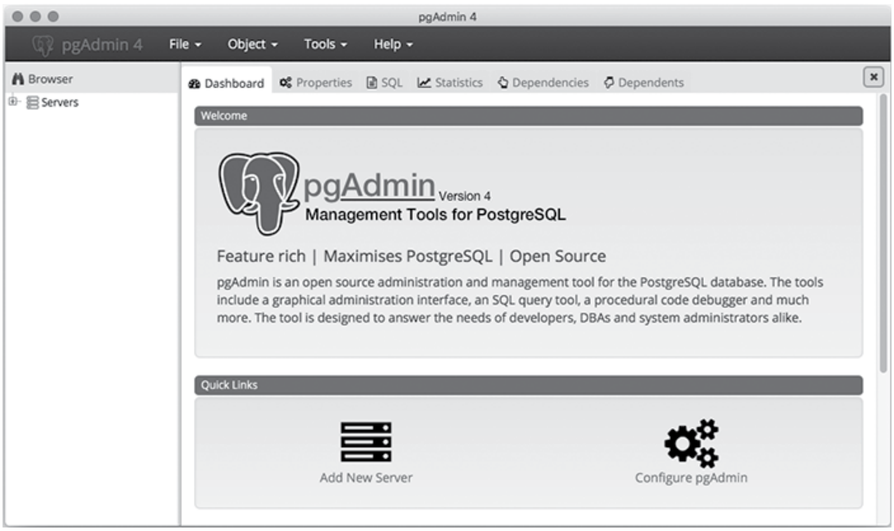


Figure 0-1: The macOS version of the pgAdmin opening screen

The left vertical pane displays an Object Browser where you can view available servers, databases, users, and other objects. Across the top of the screen is a collection of menu items, and below those are tabs to display various aspects of database objects and performance.

Next, use the following steps to connect to the default database:

1. In the Object Browser, expand the plus sign (+) to the left of the Servers node to show the default server. Depending on your operating system, the default server name could be *localhost* or *PostgreSQL x*, where *x* is the Postgres version number.

2. Double-click the server name. Enter the password you chose during installation if prompted. A brief message appears while pgAdmin is establishing a connection. When you're connected, several new object items should display under the server name.
3. Expand *Databases* and then expand the default database `postgres`.
4. Under `postgres`, expand the *Schemas* object, and then expand *public*.

   Your Object Browser pane should look similar to Figure 0-2.

NOTE *If pgAdmin doesn't show a default under Servers, you'll need to add it. Right-click Servers, and choose the Create Server option. In the dialog, type a name for your server in the General tab. On the Connection tab, in the Host name/address box, type* `localhost`. *Click* ***Save***, *and you should see your server listed.*

This collection of objects defines every feature of your database server. There's a lot here, but for now we'll focus on the location of tables. To view a table's structure or perform actions on it with pgAdmin, this is where you can access the table. In Chapter 1, you'll use this Browser to create a new database and leave the default `postgres` as is.

In addition, pgAdmin includes a *Query Tool*, which is where you write and execute code. To open the Query Tool, in pgAdmin's Object Browser, click once on any database to highlight it. For example, click the `postgres` database and then select **Tools ▸ Query Tool**. The Query Tool has two panes: one for writing queries and one for output.

It's possible to open multiple tabs to connect to and write queries for different databases or just to organize your code the way you would like. To open another tab, click another database in the Object Browser and open the Query Tool again via the menu.

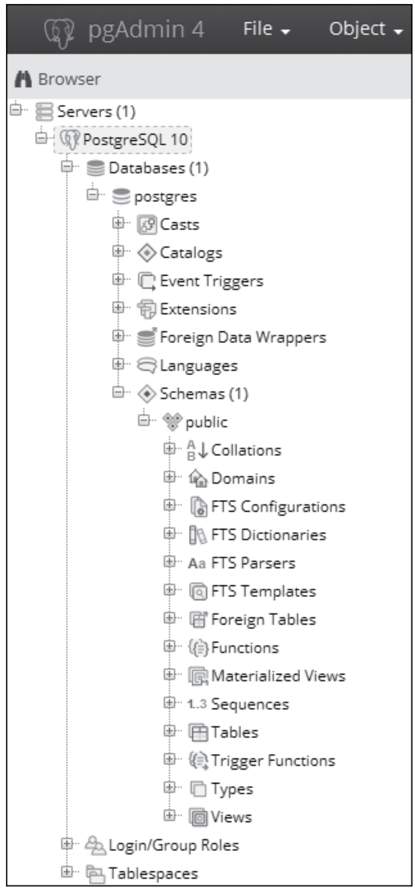


Figure 0-2: The pgAdmin Object Browser

Alternatives to pgAdmin

Although pgAdmin is great for beginners, you're not required to use it. If you prefer another administrative tool that works with PostgreSQL, feel free to use it. If you want to use your system's command line for all the exercises in this book, Chapter 16 provides instructions on using the PostgreSQL command line tool `psql`. (Appendix B lists PostgreSQL resources you can explore to find additional administrative tools.)

Wrapping Up

Now that you've installed PostgreSQL and pgAdmin, you're ready to start learning SQL and use it to discover valuable insights into your data!

In Chapter 1, you'll learn how to create a database and a table, and then you'll load some data to explore its contents. Let's get started!

1

CREATING YOUR FIRST DATABASE AND TABLE

SQL is more than just a means for extracting knowledge from data. It's also a language for *defining* the structures that hold data so we can organize *relationships* in the data. Chief among those structures is the table.

A table is a grid of rows and columns that store data. Each row holds a collection of columns, and each column contains data of a specified type: most commonly, numbers, characters, and dates. We use SQL to define the structure of a table and how each table might relate to other tables in the database. We also use SQL to extract, or *query*, data from tables.

Understanding tables is fundamental to understanding the data in your database. Whenever I start working with a fresh database, the first thing I do is look at the tables within. I look for clues in the table names and their column structure. Do the tables contain text, numbers, or both? How many rows are in each table?

Next, I look at how many tables are in the database. The simplest database might have a single table. A full-bore application that handles customer data or tracks air travel might have dozens or hundreds. The number of tables tells me not only how much data I'll need to analyze, but also hints that I should explore relationships among the data in each table.

Before you dig into SQL, let's look at an example of what the contents of tables might look like. We'll use a hypothetical database for managing a school's class enrollment; within that database are several tables that track students and their classes. The first table, called `student_enrollment`, shows the students that are signed up for each class section:

```
student_id    class_id      class_section    semester
----------    ----------    -------------    ---------
CHRISPA004    COMPSCI101    3                Fall 2017
DAVISHE010    COMPSCI101    3                Fall 2017
ABRILDA002    ENG101        40               Fall 2017
DAVISHE010    ENG101        40               Fall 2017
RILEYPH002    ENG101        40               Fall 2017
```

This table shows that two students have signed up for `COMPSCI101`, and three have signed up for `ENG101`. But where are the details about each student and class? In this example, these details are stored in separate tables called `students` and `classes`, and each table relates to this one. This is where the power of a *relational database* begins to show itself.

The first several rows of the `students` table include the following:

```
student_id    first_name    last_name    dob
----------    ----------    ---------    ----------
ABRILDA002    Abril         Davis        1999-01-10
CHRISPA004    Chris         Park         1996-04-10
DAVISHE010    Davis         Hernandez    1987-09-14
RILEYPH002    Riley         Phelps       1996-06-15
```

The `students` table contains details on each student, using the value in the `student_id` column to identify each one. That value acts as a unique *key* that connects both tables, giving you the ability to create rows such as the following with the `class_id` column from `student_enrollment` and the `first_name` and `last_name` columns from `students`:

```
class_id      first_name    last_name
----------    ----------    ---------
COMPSCI101    Davis         Hernandez
COMPSCI101    Chris         Park
ENG101        Abril         Davis
ENG101        Davis         Hernandez
ENG101        Riley         Phelps
```

The `classes` table would work the same way, with a `class_id` column and several columns of detail about the class. Database builders prefer to organize data using separate tables for each main *entity* the database manages in order to reduce redundant data. In the example, we store each student's name and date of birth just once. Even if the student signs up for multiple classes—as Davis Hernandez did—we don't waste database space entering his name next to each class in the `student_enrollment` table. We just include his student ID.

Given that tables are a core building block of every database, in this chapter you'll start your SQL coding adventure by creating a table inside a new database. Then you'll load data into the table and view the completed table.

Create a Database

The PostgreSQL program you downloaded in the Introduction is a *database management system*, a software package that allows you to define, manage, and query databases. When you installed PostgreSQL, it created a *database server*—an instance of the application running on your computer—that includes a default database called `postgres`. The database is a collection of objects that includes tables, functions, user roles, and much more. According to the PostgreSQL documentation, the default database is "meant for use by users, utilities and third party applications" (see *https://www.postgresql.org/docs/current/static/app-initdb.html*). In the exercises in this chapter, we'll leave the default as is and instead create a new one. We'll do this to keep objects related to a particular topic or application organized together.

To create a database, you use just one line of SQL, shown in Listing 1-1. This code, along with all the examples in this book, is available for download via the resources at *https://www.nostarch.com/practicalSQL/*.

```
CREATE DATABASE analysis;
```

Listing 1-1: Creating a database named `analysis`

This statement creates a database on your server named `analysis` using default PostgreSQL settings. Note that the code consists of two keywords—`CREATE` and `DATABASE`—followed by the name of the new database. The statement ends with a semicolon, which signals the end of the command. The semicolon ends all PostgreSQL statements and is part of the ANSI SQL standard. Sometimes you can omit the semicolon, but not always, and particularly not when running multiple statements in the admin. So, using the semicolon is a good habit to form.

Executing SQL in pgAdmin

As part of the Introduction to this book, you also installed the graphical administrative tool pgAdmin (if you didn't, go ahead and do that now). For much of our work, you'll use pgAdmin to run (or execute) the SQL statements we write. Later in the book in Chapter 16, I'll show you how to run SQL statements in a terminal window using the PostgreSQL command-line program `psql`, but getting started is a bit easier with a graphical interface.

We'll use pgAdmin to run the SQL in Listing 1-1 that creates the database. Then, we'll connect to the new database and create a table. Follow these steps:

1. Run PostgreSQL. If you're using Windows, the installer set PostgreSQL to launch every time you boot up. On macOS, you must double-click *Postgres.app* in your Applications folder.
2. Launch pgAdmin. As you did in the Introduction, in the left vertical pane (the object browser) expand the plus sign to the left of the Servers node to show the default server. Depending on how you installed PostgreSQL, the default server may be named *localhost* or *PostgreSQL x*, where *x* is the version of the application.
3. Double-click the server name. If you supplied a password during installation, enter it at the prompt. You'll see a brief message that pgAdmin is establishing a connection.
4. In pgAdmin's object browser, expand **Databases** and click once on the `postgres` database to highlight it, as shown in Figure 1-1.
5. Open the Query Tool by choosing **Tools ▸ Query Tool**.
6. In the SQL Editor pane (the top horizontal pane), type or copy the code from Listing 1-1.
7. Click the lightning bolt icon to execute the SQL. PostgreSQL creates the database, and in the Output pane in the Query Tool under Messages you'll see a notice indicating the query returned successfully, as shown in Figure 1-2.

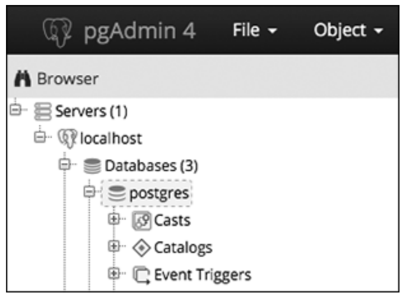


Figure 1-1: Connecting to the default postgres database

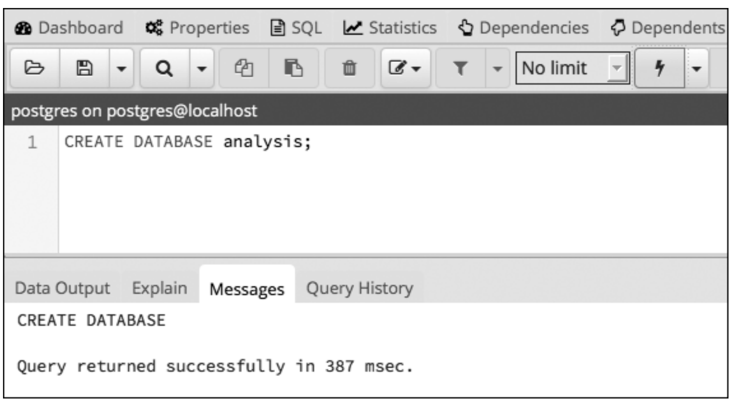


Figure 1-2: Creating the `analysis` database

8. To see your new database, right-click **Databases** in the object browser. From the pop-up menu, select **Refresh**, and the `analysis` database will appear in the list, as shown in Figure 1-3.

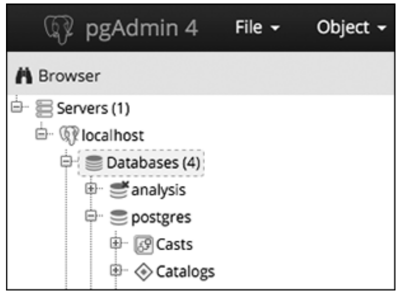


Figure 1-3: The `analysis` *database displayed in the object browser*

Good work! You now have a database called `analysis`, which you can use for the majority of the exercises in this book. In your own work, it's generally a best practice to create a new database for each project to keep tables with related data together.

Connecting to the Analysis Database

Before you create a table, you must ensure that pgAdmin is connected to the `analysis` database rather than to the default `postgres` database.

To do that, follow these steps:

1. Close the Query Tool by clicking the **X** at the top right of the tool.
2. In the object browser, click once on the `analysis` database.
3. Reopen the Query Tool by choosing **Tools** ▸ **Query Tool**.
4. You should now see the label `analysis on postgres@localhost` at the top of the Query Tool window. (Again, instead of `localhost`, your version may show `PostgreSQL`.)

Now, any code you execute will apply to the `analysis` database.

Create a Table

As I mentioned earlier, tables are where data lives and its relationships are defined. When you create a table, you assign a name to each *column* (sometimes referred to as a *field* or *attribute*) and assign it a *data type*. These are the values the column will accept—such as text, integers, decimals, and dates—and the definition of the data type is one way SQL enforces the integrity of data. For example, a column defined as `date` will take data in one of several standard formats, such as `YYYY-MM-DD`. If you try to enter characters not in a date format, for instance, the word `peach`, you'll receive an error.

Data stored in a table can be accessed and analyzed, or queried, with SQL statements. You can sort, edit, and view the data, and easily alter the table later if your needs change.

Let's make a table in the `analysis` database.

The CREATE TABLE Statement

For this exercise, we'll use an often-discussed piece of data: teacher salaries. Listing 1-2 shows the SQL to create a table called teachers:

```
❶ CREATE TABLE teachers (
❷     id bigserial,
❸     first_name varchar(25),
      last_name varchar(50),
      school varchar(50),
❹     hire_date date,
❺     salary numeric
❻ );
```

Listing 1-2: Creating a table named teachers with six columns

This table definition is far from comprehensive. For example, it's missing several *constraints* that would ensure that columns that must be filled do indeed have data or that we're not inadvertently entering duplicate values. I cover constraints in detail in Chapter 7, but in these early chapters I'm omitting them to focus on getting you started on exploring data.

The code begins with the two SQL keywords ❶ `CREATE` and `TABLE` that, together with the name `teachers`, signal PostgreSQL that the next bit of code describes a table to add to the database. Following an opening parenthesis, the statement includes a comma-separated list of column names along with their data types. For style purposes, each new line of code is on its own line and indented four spaces, which isn't required, but it makes the code more readable.

Each column name represents one discrete data element defined by a data type. The `id` column ❷ is of data type `bigserial`, a special integer type that auto-increments every time you add a row to the table. The first row receives the value of `1` in the `id` column, the second row `2`, and so on. The `bigserial` data type and other serial types are PostgreSQL-specific implementations, but most database systems have a similar feature.

Next, we create columns for the teacher's first and last name, and the school where they teach ❸. Each is of the data type `varchar`, a text column with a maximum length specified by the number in parentheses. We're assuming that no one in the database will have a last name of more than 50 characters. Although this is a safe assumption, you'll discover over time that exceptions will always surprise you.

The teacher's `hire_date` ❹ is set to the data type `date`, and the `salary` column ❺ is a `numeric`. I'll cover data types more thoroughly in Chapter 3, but this table shows some common examples of data types. The code block wraps up ❻ with a closing parenthesis and a semicolon.

Now that you have a sense of how SQL looks, let's run this code in pgAdmin.

Making the teachers Table

You have your code and you're connected to the database, so you can make the table using the same steps we did when we created the database:

1. Open the pgAdmin Query Tool (if it's not open, click once on the `analysis` database in pgAdmin's object browser, and then choose **Tools ▸ Query Tool**).
2. Copy the `CREATE TABLE` script from Listing 1-2 into the SQL Editor.
3. Execute the script by clicking the lightning bolt icon.

If all goes well, you'll see a message in the pgAdmin Query Tool's bottom output pane that reads, `Query returned successfully with no result in 84 msec`. Of course, the number of milliseconds will vary depending on your system.

Now, find the table you created. Go back to the main pgAdmin window and, in the object browser, right-click the `analysis` database and choose **Refresh**. Choose **Schemas ▸ public ▸ Tables** to see your new table, as shown in Figure 1-4.

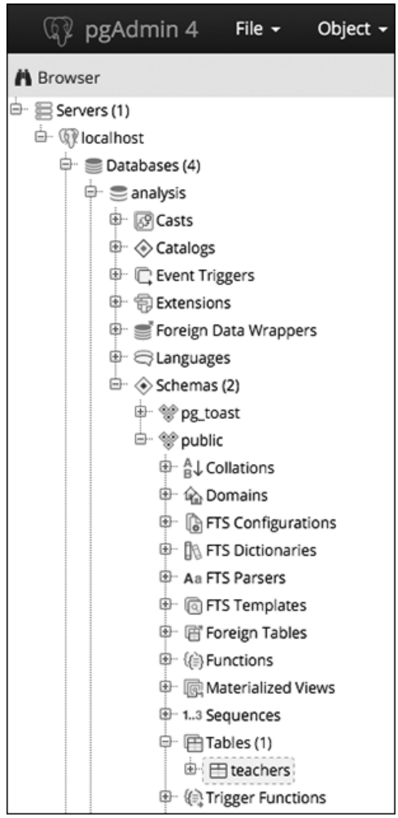


Figure 1-4: The teachers table in the object browser

Expand the `teachers` table node by clicking the plus sign to the left of its name. This reveals more details about the table, including the column names, as shown in Figure 1-5. Other information appears as well, such as indexes, triggers, and constraints, but I'll cover those in later chapters. Clicking on the table name and then selecting the **SQL** menu in the pgAdmin workspace will display the SQL used to make the `teachers` table.

Congratulations! So far, you've built a database and added a table to it. The next step is to add data to the table so you can write your first query.

Insert Rows into a Table

You can add data to a PostgreSQL table in several ways. Often, you'll work with a large number of rows, so the easiest method is to import data from a text file or another database directly into a table. But just to get started, we'll add a few rows using an `INSERT INTO ... VALUES` statement that specifies the target columns and the data values. Then we'll view the data in its new home.

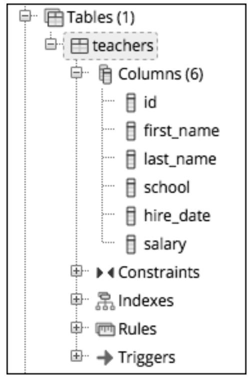


Figure 1-5: Table details for teachers

The INSERT Statement

To insert some data into the table, you first need to erase the `CREATE TABLE` statement you just ran. Then, following the same steps as you did to create the database and table, copy the code in Listing 1-3 into your pgAdmin Query Tool:

```
❶ INSERT INTO teachers (first_name, last_name, school, hire_date, salary)
❷ VALUES ('Janet', 'Smith', 'F.D. Roosevelt HS', '2011-10-30', 36200),
         ('Lee', 'Reynolds', 'F.D. Roosevelt HS', '1993-05-22', 65000),
         ('Samuel', 'Cole', 'Myers Middle School', '2005-08-01', 43500),
         ('Samantha', 'Bush', 'Myers Middle School', '2011-10-30', 36200),
         ('Betty', 'Diaz', 'Myers Middle School', '2005-08-30', 43500),
         ('Kathleen', 'Roush', 'F.D. Roosevelt HS', '2010-10-22', 38500);❸
```

Listing 1-3: Inserting data into the teachers table

This code block inserts names and data for six teachers. Here, the PostgreSQL syntax follows the ANSI SQL standard: after the `INSERT INTO` keywords is the name of the table, and in parentheses are the columns to be filled ❶. In the next row is the `VALUES` keyword and the data to insert into each column in each row ❷. You need to enclose the data for each row in a set of parentheses, and inside each set of parentheses, use a comma to separate each column value. The order of the values must also match the order of the columns specified after the table name. Each row of data ends with a comma, and the last row ends the entire statement with a semicolon ❸.

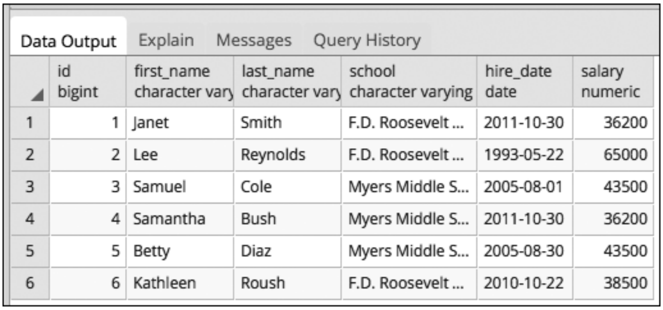
Notice that certain values that we're inserting are enclosed in single quotes, but some are not. This is a standard SQL requirement. Text and dates require quotes; numbers, including integers and decimals, don't require quotes. I'll highlight this requirement as it comes up in examples. Also, note the date format we're using: a four-digit year is followed by the month and date, and each part is joined by a hyphen. This is the international standard for date formats; using it will help you avoid confusion. (Why is it best to use the format `YYYY-MM-DD`? Check out *https://xkcd.com/1179/* to see a great comic about it.) PostgreSQL supports many additional date formats, and I'll use several in examples.

You might be wondering about the `id` column, which is the first column in the table. When you created the table, your script specified that column to be the `serial` data type. So as PostgreSQL inserts each row, it automatically fills the `id` column with an auto-incrementing integer. I'll cover that in detail in Chapter 3 when I discuss data types.

Now, run the code. This time the message in the Query Tool should include the words `Query returned successfully: 6 rows affected.`

Viewing the Data

You can take a quick look at the data you just loaded into the `teachers` table using pgAdmin. In the object browser, locate the table and right-click. In the pop-up menu, choose **View/Edit Data ▸ All Rows**. As Figure 1-6 shows, you'll see the six rows of data in the table with each column filled by the values in the SQL statement.



	id bigint	first_name character vary	last_name character vary	school character varying	hire_date date	salary numeric
1	1	Janet	Smith	F.D. Roosevelt ...	2011-10-30	36200
2	2	Lee	Reynolds	F.D. Roosevelt ...	1993-05-22	65000
3	3	Samuel	Cole	Myers Middle S...	2005-08-01	43500
4	4	Samantha	Bush	Myers Middle S...	2011-10-30	36200
5	5	Betty	Diaz	Myers Middle S...	2005-08-30	43500
6	6	Kathleen	Roush	F.D. Roosevelt ...	2010-10-22	38500

Figure 1-6: Viewing table data directly in pgAdmin

Notice that even though you didn't insert a value for the `id` column, each teacher has an id number assigned.

pgAdmin lets you view data using this interface in a few ways, but we'll focus on writing SQL to handle those tasks.

When Code Goes Bad

There may be a universe where code always works, but unfortunately, we haven't invented a machine capable of transporting us there. Errors happen. Whether you make a typo or mix up the order of operations, computer languages are unforgiving about syntax. For example, if you forget a comma in the code in Listing 1-3, PostgreSQL squawks back an error:

```
ERROR:  syntax error at or near "("
LINE 5:     ('Samuel', 'Cole', 'Myers Middle School', '2005-08-01', 43...
            ^
********** Error **********
```

Fortunately, the error message hints at what's wrong and where: a syntax error is near an open parenthesis on line 5. But sometimes error messages can be more obscure. In that case, you do what the best coders do: a quick internet search for the error message. Most likely, someone else has experienced the same issue and might know the answer.

Formatting SQL for Readability

SQL requires no special formatting to run, so you're free to use your own psychedelic style of uppercase, lowercase, and random indentations. But that won't win you any friends when others need to work with your code (and sooner or later someone will). For the sake of readability and being a good coder, it's best to follow these conventions:

- Uppercase SQL keywords, such as `SELECT`. Some SQL coders also uppercase the names of data types, such as `TEXT` and `INTEGER`. I use lowercase characters for data types in this book to separate them in your mind from keywords, but you can uppercase them if desired.
- Avoid `CamelCase` and instead use `lowercase_and_underscores` for object names, such as tables and column names (see more details about case in Chapter 7).
- Indent clauses and code blocks for readability using either two or four spaces. Some coders prefer tabs to spaces; use whichever works best for you or your organization.

We'll explore other SQL coding conventions as we go through the book, but these are the basics.

Wrapping Up

You accomplished quite a bit in this first chapter: you created a database and a table, and then loaded data into it. You're on your way to adding SQL to your data analysis toolkit! In the next chapter, you'll use this set of teacher data to learn the basics of querying a table using `SELECT`.

Try It Yourself

Here are two exercises to help you explore concepts related to databases, tables, and data relationships:

1. Imagine you're building a database to catalog all the animals at your local zoo. You want one table to track the kinds of animals in the collection and another table to track the specifics on each animal. Write `CREATE TABLE` statements for each table that include some of the columns you need. Why did you include the columns you chose?
2. Now create `INSERT` statements to load sample data into the tables. How can you view the data via the pgAdmin tool? Create an additional `INSERT` statement for one of your tables. Purposely omit one of the required commas separating the entries in the `VALUES` clause of the query. What is the error message? Would it help you find the error in the code?

2

BEGINNING DATA EXPLORATION WITH SELECT

For me, the best part of digging into data isn't the prerequisites of gathering, loading, or cleaning the data, but when I actually get to *interview* the data. Those are the moments when I discover whether the data is clean or dirty, whether it's complete, and most of all, what story the data can tell. Think of interviewing data as a process akin to interviewing a person applying for a job. You want to ask questions that reveal whether the reality of their expertise matches their resume.

Interviewing is exciting because you discover truths. For example, you might find that half the respondents forgot to fill out the email field in the questionnaire, or the mayor hasn't paid property taxes for the past five years. Or you might learn that your data is dirty: names are spelled inconsistently, dates are incorrect, or numbers don't jibe with your expectations. Your findings become part of the data's story.

In SQL, interviewing data starts with the `SELECT` keyword, which retrieves rows and columns from one or more of the tables in a database. A

SELECT statement can be simple, retrieving everything in a single table, or it can be complex enough to link dozens of tables while handling multiple calculations and filtering by exact criteria.

We'll start with simple SELECT statements.

Basic SELECT Syntax

Here's a SELECT statement that fetches every row and column in a table called my_table:

```
SELECT * FROM my_table;
```

This single line of code shows the most basic form of a SQL query. The asterisk following the SELECT keyword is a *wildcard*. A wildcard is like a stand-in for a value: it doesn't represent anything in particular and instead represents everything that value could possibly be. Here, it's shorthand for "select all columns." If you had given a column name instead of the wildcard, this command would select the values in that column. The FROM keyword indicates you want the query to return data from a particular table. The semicolon after the table name tells PostgreSQL it's the end of the query statement.

Let's use this SELECT statement with the asterisk wildcard on the teachers table you created in Chapter 1. Once again, open pgAdmin, select the analysis database, and open the Query Tool. Then execute the statement shown in Listing 2-1:

```
SELECT * FROM teachers;
```

Listing 2-1: Querying all rows and columns from the teachers table

The result set in the Query Tool's output pane contains all the rows and columns you inserted into the teachers table in Chapter 1. The rows may not always appear in this order, but that's okay.

```
id    first_name    last_name    school                 hire_date     salary
--    ----------    ---------    -------------------    ----------    ------
1     Janet         Smith        F.D. Roosevelt HS      2011-10-30    36200
2     Lee           Reynolds     F.D. Roosevelt HS      1993-05-22    65000
3     Samuel        Cole         Myers Middle School    2005-08-01    43500
4     Samantha      Bush         Myers Middle School    2011-10-30    36200
5     Betty         Diaz         Myers Middle School    2005-08-30    43500
6     Kathleen      Roush        F.D. Roosevelt HS      2010-10-22    38500
```

Note that the id column (of type serial) automatically fills with sequential integers, even though you didn't explicitly insert them. Very handy. This auto-incrementing integer acts as a unique identifier, or key, that not only ensures each row in the table is unique, but also will later give us a way to connect this table to other tables in the database.

Let's move on to refining this query.

Querying a Subset of Columns

Using the asterisk wildcard is helpful for discovering the entire contents of a table. But often it's more practical to limit the columns the query retrieves, especially with large databases. You can do this by naming columns, separated by commas, right after the SELECT keyword. For example:

```
SELECT some_column, another_column, amazing_column FROM table_name;
```

With that syntax, the query will retrieve all rows from just those three columns.

Let's apply this to the teachers table. Perhaps in your analysis you want to focus on teachers' names and salaries, not the school where they work or when they were hired. In that case, you might select only a few columns from the table instead of using the asterisk wildcard. Enter the statement shown in Listing 2-2. Notice that the order of the columns in the query is different than the order in the table: you're able to retrieve columns in any order you'd like.

```
SELECT last_name, first_name, salary FROM teachers;
```

Listing 2-2: Querying a subset of columns

Now, in the result set, you've limited the columns to three:

```
last_name    first_name    salary
---------    ----------    ------
Smith        Janet         36200
Reynolds     Lee           65000
Cole         Samuel        43500
Bush         Samantha      36200
Diaz         Betty         43500
Roush        Kathleen      38500
```

Although these examples are basic, they illustrate a good strategy for beginning your interview of a data set. Generally, it's wise to start your analysis by checking whether your data is present and in the format you expect. Are dates in a complete month-date-year format, or are they entered (as I once ruefully observed) as text with the month and year only? Does every row have a value? Are there mysteriously no last names starting with letters beyond "M"? All these issues indicate potential hazards ranging from missing data to shoddy recordkeeping somewhere in the workflow.

We're only working with a table of six rows, but when you're facing a table of thousands or even millions of rows, it's essential to get a quick read on your data quality and the range of values it contains. To do this, let's dig deeper and add several SQL keywords.

Using DISTINCT to Find Unique Values

In a table, it's not unusual for a column to contain rows with duplicate values. In the `teachers` table, for example, the `school` column lists the same school names multiple times because each school employs many teachers.

To understand the range of values in a column, we can use the `DISTINCT` keyword as part of a query that eliminates duplicates and shows only unique values. Use the `DISTINCT` keyword immediately after `SELECT`, as shown in Listing 2-3:

```
SELECT DISTINCT school
FROM teachers;
```

Listing 2-3: Querying distinct values in the `school` *column*

The result is as follows:

```
school
-------------------
F.D. Roosevelt HS
Myers Middle School
```

Even though six rows are in the table, the output shows just the two unique school names in the `school` column. This is a helpful first step toward assessing data quality. For example, if a school name is spelled more than one way, those spelling variations will be easy to spot and correct. When you're working with dates or numbers, `DISTINCT` will help highlight inconsistent or broken formatting. For example, you might inherit a data set in which dates were entered in a column formatted with a text data type. That practice (which you should avoid) allows malformed dates to exist:

```
date
---------
5/30/2015
6//2015
6/1/2015
6/2/2015
```

The `DISTINCT` keyword also works on more than one column at a time. If we add a column, the query returns each unique pair of values. Run the code in Listing 2-4:

```
SELECT DISTINCT school, salary
FROM teachers;
```

Listing 2-4: Querying distinct pairs of values in the `school` *and* `salary` *columns*

Now the query returns each unique (or distinct) salary earned at each school. Because two teachers at Myers Middle School earn $43,500, that pair is listed in just one row, and the query returns five rows rather than all six in the table:

```
school                salary
-------------------   ------
Myers Middle School   43500
Myers Middle School   36200
F.D. Roosevelt HS     65000
F.D. Roosevelt HS     38500
F.D. Roosevelt HS     36200
```

This technique gives us the ability to ask, "For each *x* in the table, what are all the *y* values?" For each factory, what are all the chemicals it produces? For each election district, who are all the candidates running for office? For each concert hall, who are the artists playing this month?

SQL offers more sophisticated techniques with aggregate functions that let us count, sum, and find minimum and maximum values. I'll cover those in detail in later chapters.

Sorting Data with ORDER BY

Data can make more sense, and may reveal patterns more readily, when it's arranged in order rather than jumbled randomly.

In SQL, we order the results of a query using a clause containing the keywords `ORDER BY` followed by the name of the column or columns to sort. Applying this clause doesn't change the original table, only the result of the query. Listing 2-5 shows an example using the `teachers` table:

```
SELECT first_name, last_name, salary
FROM teachers
ORDER BY salary DESC;
```

Listing 2-5: Sorting a column with `ORDER BY`

By default, `ORDER BY` sorts values in ascending order, but here I sort in descending order by adding the `DESC` keyword. (The optional `ASC` keyword specifies sorting in ascending order.) Now, by ordering the `salary` column from highest to lowest, I can determine which teachers earn the most:

```
first_name   last_name   salary
----------   ---------   ------
Lee          Reynolds    65000
Samuel       Cole        43500
Betty        Diaz        43500
Kathleen     Roush       38500
Janet        Smith       36200
Samantha     Bush        36200
```

SORTING TEXT MAY SURPRISE YOU

Sorting a column of numbers in PostgreSQL yields what you might expect: the data ranked from largest value to smallest or vice versa depending on whether or not you use the `DESC` keyword. But sorting a column with letters or other characters may return surprising results, especially if it has a mix of uppercase and lowercase characters, punctuation, or numbers that are treated as text.

During PostgreSQL installation, the server is assigned a particular *locale* for *collation*, or ordering of text, as well as a *character set*. Both are based either on settings in the computer's operating system or custom options supplied during installation. (You can read more about collation in the official PostgreSQL documentation at *https://www.postgresql.org/docs/current/static/collation.html*.) On my Mac, my PostgreSQL install is set to the locale en_US, or U.S. English, and the character set UTF-8. I'll cover how to change this setting in Chapter 17.

In a character set, each character gets a numerical value, and the sorting order depends on the order of those values. Based on UTF-8, PostgreSQL sorts characters in this order:

1. Punctuation marks, including quotes, parentheses, and math operators
2. Numbers 0 to 9
3. Additional punctuation, including the question mark
4. Capital letters from A to Z
5. More punctuation, including brackets and underscore _
6. Lowercase letters a to z
7. Additional punctuation, special characters, and the extended alphabet

Normally, the sorting order won't be an issue because character columns usually just contain names, places, descriptions, and other straightforward text. But if you're wondering why the word *Ladybug* appears before *ladybug* in your sort, you now have an explanation.

The ability to sort in our queries gives us great flexibility in how we view and present data. For example, we're not limited to sorting on just one column. Enter the statement in Listing 2-6:

```
SELECT last_name, school, hire_date
FROM teachers
❶ ORDER BY school ASC, hire_date DESC;
```

Listing 2-6: Sorting multiple columns with `ORDER BY`

In this case, we're retrieving the last names of teachers, their school, and the date they were hired. By sorting the `school` column in ascending order and `hire_date` in descending ❶, we create a listing of teachers grouped by school with the most recently hired teachers listed first. This shows us who the newest teachers are at each school. The result set should look like this:

```
last_name    school                 hire_date
---------    -------------------    ----------
Smith        F.D. Roosevelt HS      2011-10-30
Roush        F.D. Roosevelt HS      2010-10-22
Reynolds     F.D. Roosevelt HS      1993-05-22
Bush         Myers Middle School    2011-10-30
Diaz         Myers Middle School    2005-08-30
Cole         Myers Middle School    2005-08-01
```

You can `ORDER BY` more than two columns, but you'll soon reach a point of diminishing returns where the effect will be hardly noticeable. Imagine if you added columns about teachers' highest college degree attained, the grade level taught, and birth date to the `ORDER BY` clause. It would be difficult to understand the various sort directions in the output all at once, much less communicate that to others. Digesting data happens most easily when the result focuses on answering a specific question; therefore, a better strategy is to limit the number of columns in your query to only the most important, and then run several queries to answer each question you have.

Filter Rows with WHERE

Sometimes, you'll want to limit the rows a query returns to only those in which one or more columns meet certain criteria. Using `teachers` as an example, you might want to find all teachers hired before a particular year or all teachers making more than $75,000 at elementary schools. For these tasks, we use the `WHERE` clause.

The `WHERE` keyword allows you to find rows that match a specific value, a range of values, or multiple values based on criteria supplied via an *operator*. You also can exclude rows based on criteria.

Listing 2-7 shows a basic example. Note that in standard SQL syntax, the `WHERE` clause follows the `FROM` keyword and the name of the table or tables being queried:

```
SELECT last_name, school, hire_date
FROM teachers
WHERE school = 'Myers Middle School';
```

Listing 2-7: Filtering rows using `WHERE`

The result set shows just the teachers assigned to Myers Middle School:

```
last_name    school                 hire_date
---------    -------------------    ----------
Cole         Myers Middle School    2005-08-01
Bush         Myers Middle School    2011-10-30
Diaz         Myers Middle School    2005-08-30
```

Here, I'm using the equals comparison operator to find rows that exactly match a value, but of course you can use other operators with `WHERE` to customize your filter criteria. Table 2-1 provides a summary of the most commonly used comparison operators. Depending on your database system, many more might be available.

Table 2-1: SQL Comparison Operators in PostgreSQL

Operator	Function	Example
=	Equals	WHERE school = 'Baker Middle'
<> or !=*	Not equal	WHERE school <> 'Baker Middle'
>	Greater than	WHERE salary > 20000
<	Less than	WHERE salary < 60500
>=	Greater than or equals	WHERE salary >= 20000
<=	Less than or equals	WHERE salary <= 60500
BETWEEN	Within a range	WHERE salary BETWEEN 20000 AND 40000
IN	Match one of a set of values	WHERE last_name IN ('Bush', 'Roush')
LIKE	Match a pattern (case-sensitive)	WHERE first_name LIKE 'Sam%'
ILIKE	Match a pattern (case-insensitive)	WHERE first_name ILIKE 'sam%'
NOT	Negates a condition	WHERE first_name NOT ILIKE 'sam%'

* The != operator is not part of standard ANSI SQL but is available in PostgreSQL and several other database systems

The following examples show comparison operators in action. First, we use the equals operator to find teachers whose first name is Janet:

```
SELECT first_name, last_name, school
FROM teachers
WHERE first_name = 'Janet';
```

Next, we list all school names in the table but exclude F.D. Roosevelt HS using the not equal operator:

```
SELECT school
FROM teachers
WHERE school != 'F.D. Roosevelt HS';
```

Here we use the less than operator to list teachers hired before January 1, 2000 (using the date format `YYYY-MM-DD`):

```
SELECT first_name, last_name, hire_date
FROM teachers
WHERE hire_date < '2000-01-01';
```

Then we find teachers who earn $43,500 or more using the greater than or equals operator:

```
SELECT first_name, last_name, salary
FROM teachers
WHERE salary >= 43500;
```

The next query uses the `BETWEEN` operator to find teachers who earn between $40,000 and $65,000. Note that `BETWEEN` is *inclusive*, meaning the result will include values matching the start and end ranges specified.

```
SELECT first_name, last_name, school, salary
FROM teachers
WHERE salary BETWEEN 40000 AND 65000;
```

We'll return to these operators throughout the book, because they'll play a key role in helping us ferret out the data and answers we want to find.

Using LIKE and ILIKE with WHERE

Comparison operators are fairly straightforward, but `LIKE` and `ILIKE` deserve additional explanation. First, both let you search for patterns in strings by using two special characters:

Percent sign (%) A wildcard matching one or more characters

Underscore (_) A wildcard matching just one character

For example, if you're trying to find the word `baker`, the following `LIKE` patterns will match it:

```
LIKE 'b%'
LIKE '%ak%'
LIKE '_aker'
LIKE 'ba_er'
```

The difference? The `LIKE` operator, which is part of the ANSI SQL standard, is case-sensitive. The `ILIKE` operator, which is a PostgreSQL-only implementation, is case-insensitive. Listing 2-8 shows how the two keywords give you different results. The first `WHERE` clause uses `LIKE` ❶ to find names that start with the characters `sam`, and because it's case-sensitive, it will return zero results. The second, using the case-insensitive `ILIKE` ❷, will return `Samuel` and `Samantha` from the table:

```
  SELECT first_name
  FROM teachers
❶ WHERE first_name LIKE 'sam%';

  SELECT first_name
```

```
FROM teachers
❷ WHERE first_name ILIKE 'sam%';
```

Listing 2-8: Filtering with `LIKE` and `ILIKE`

Over the years, I've gravitated toward using `ILIKE` and wildcard operators in searches to make sure I'm not inadvertently excluding results from searches. I don't assume that whoever typed the names of people, places, products, or other proper nouns always remembered to capitalize them. And if one of the goals of interviewing data is to understand its quality, using a case-insensitive search will help you find variations.

Because `LIKE` and `ILIKE` search for patterns, performance on large databases can be slow. We can improve performance using indexes, which I'll cover in Chapter 7.

Combining Operators with AND and OR

Comparison operators become even more useful when we combine them. To do this, we connect them using keywords `AND` and `OR` along with, if needed, parentheses.

The statements in Listing 2-9 show three examples that combine operators this way:

```
SELECT *
FROM teachers
❶ WHERE school = 'Myers Middle School'
      AND salary < 40000;

SELECT *
FROM teachers
❷ WHERE last_name = 'Cole'
      OR last_name ='Bush';

SELECT *
FROM teachers
❸ WHERE school = 'F.D. Roosevelt HS'
      AND (salary < 38000 OR salary > 40000);
```

Listing 2-9: Combining operators using `AND` and `OR`

The first query uses `AND` in the `WHERE` clause ❶ to find teachers who work at Myers Middle School and have a salary less than $40,000. Because we connect the two conditions using `AND`, both must be true for a row to meet the criteria in the `WHERE` clause and be returned in the query results.

The second example uses `OR` ❷ to search for any teacher whose last name matches Cole or Bush. When we connect conditions using `OR`, only one of the conditions must be true for a row to meet the criteria of the `WHERE` clause.

The final example looks for teachers at Roosevelt whose salaries are either less than $38,000 or greater than $40,000 ❸. When we place statements inside parentheses, those are evaluated as a group before being combined with other criteria. In this case, the school name must be exactly `F.D. Roosevelt HS` and the salary must be either less or higher than specified for a row to meet the criteria of the `WHERE` clause.

Putting It All Together

You can begin to see how even the previous simple queries allow us to delve into our data with flexibility and precision to find what we're looking for. You can combine comparison operator statements using the `AND` and `OR` keywords to provide multiple criteria for filtering, and you can include an `ORDER BY` clause to rank the results.

With the preceding information in mind, let's combine the concepts in this chapter into one statement to show how they fit together. SQL is particular about the order of keywords, so follow this convention:

```
SELECT field_names
FROM table_name
WHERE criteria
ORDER BY field_names;
```

Listing 2-10 shows a query against the `teachers` table that includes all the aforementioned pieces:

```
SELECT first_name, last_name, school, hire_date, salary
FROM teachers
WHERE school LIKE '%Roos%'
ORDER BY hire_date DESC;
```

Listing 2-10: A `SELECT` statement including `WHERE` and `ORDER BY`

This listing returns teachers at Roosevelt High School, ordered from newest hire to earliest. We can see a clear correlation between a teacher's hire date at the school and his or her current salary level:

```
first_name    last_name    school               hire_date     salary
----------    ---------    -----------------    ----------    ------
Janet         Smith        F.D. Roosevelt HS    2011-10-30    36200
Kathleen      Roush        F.D. Roosevelt HS    2010-10-22    38500
Lee           Reynolds     F.D. Roosevelt HS    1993-05-22    65000
```

Wrapping Up

Now that you've learned the basic structure of a few different SQL queries, you've acquired the foundation for many of the additional skills I'll cover in later chapters. Sorting, filtering, and choosing only the most important columns from a table can yield a surprising amount of information from your data and help you find the story it tells.

In the next chapter, you'll learn about another foundational aspect of SQL: data types.

Try It Yourself

Explore basic queries with these exercises:

1. The school district superintendent asks for a list of teachers in each school. Write a query that lists the schools in alphabetical order along with teachers ordered by last name A–Z.
2. Write a query that finds the one teacher whose first name starts with the letter S and earns more than $40,000.
3. Rank teachers hired since January 1, 2010, ordered by highest paid to lowest.

3

UNDERSTANDING DATA TYPES

Whenever I dig into a new database, I check the *data type* specified for each column in each table. If I'm lucky, I can get my hands on a *data dictionary*: a document that lists each column; specifies whether it's a number, character, or other type; and explains the column values. Unfortunately, many organizations don't create and maintain good documentation, so it's not unusual to hear, "We don't have a data dictionary." In that case, I try to learn by inspecting the table structures in pgAdmin.

It's important to understand data types because storing data in the appropriate format is fundamental to building usable databases and performing accurate analysis. In addition, a data type is a programming concept applicable to more than just SQL. The concepts you'll explore in this chapter will transfer well to additional languages you may want to learn.

In a SQL database, each column in a table can hold one and only one data type, which is defined in the `CREATE TABLE` statement. You declare the data type after naming the column. Here's a simple example that includes two columns, one a date and the other an integer:

```
CREATE TABLE eagle_watch (
    observed_date date,
    eagles_seen integer
);
```

In this table named `eagle_watch` (for an annual inventory of bald eagles), the `observed_date` column is declared to hold date values by adding the `date` type declaration after its name. Similarly, `eagles_seen` is set to hold whole numbers with the `integer` type declaration.

These data types are among the three categories you'll encounter most:

Characters Any character or symbol

Numbers Includes whole numbers and fractions

Dates and times Types holding temporal information

Let's look at each data type in depth; I'll note whether they're part of standard ANSI SQL or specific to PostgreSQL.

Characters

Character string types are general-purpose types suitable for any combination of text, numbers, and symbols. Character types include:

`char(n)`

A fixed-length column where the character length is specified by *`n`*. A column set at `char(20)` stores 20 characters per row regardless of how many characters you insert. If you insert fewer than 20 characters in any row, PostgreSQL pads the rest of that field with spaces. This type, which is part of standard SQL, also can be specified with the longer name `character(n)`. Nowadays, `char(n)` is used infrequently and is mainly a remnant of legacy computer systems.

`varchar(n)`

A variable-length column where the *maximum* length is specified by *`n`*. If you insert fewer characters than the maximum, PostgreSQL will not store extra spaces. For example, the string `blue` will take four spaces, whereas the string `123` will take three. In large databases, this practice saves considerable space. This type, included in standard SQL, also can be specified using the longer name `character varying(n)`.

`text`

A variable-length column of unlimited length. (According to the PostgreSQL documentation, the longest possible character string you can store is about 1 gigabyte.) The `text` type is not part of the SQL standard, but you'll find similar implementations in other database systems, including Microsoft SQL Server and MySQL.

According to PostgreSQL documentation at *https://www.postgresql.org/docs/current/static/datatype-character.html*, there is no substantial difference in performance among the three types. That may differ if you're using another database manager, so it's wise to check the docs. The flexibility and potential space savings of `varchar` and `text` seem to give them an advantage. But if you search discussions online, some users suggest that defining a column that will always have the same number of characters with `char` is a good way to signal what data it should contain. For instance, you might use `char(2)` for US state postal abbreviations.

To see these three character types in action, run the script in Listing 3-1. This script will build and load a simple table and then export the data to a text file on your computer.

```
CREATE TABLE char_data_types (
❶    varchar_column varchar(10),
     char_column char(10),
     text_column text
);

❷ INSERT INTO char_data_types
VALUES
    ('abc', 'abc', 'abc'),
    ('defghi', 'defghi', 'defghi');

❸ COPY char_data_types TO 'C:\YourDirectory\typetest.txt'
❹ WITH (FORMAT CSV, HEADER, DELIMITER '|');
```

Listing 3-1: Character data types in action

The script defines three character columns ❶ of different types and inserts two rows of the same string into each ❷. Unlike the `INSERT INTO` statement you learned in Chapter 1, here we're not specifying the names of the columns. If the `VALUES` statements match the number of columns in the table, the database will assume you're inserting values in the order the column definitions were specified in the table.

Next, the script uses the PostgreSQL `COPY` keyword ❸ to export the data to a text file named `typetest.txt` in a directory you specify. You'll need to replace *`C:\YourDirectory\`* with the full path to the directory on your computer where you want to save the file. The examples in this book use Windows format and a path to a directory called *`YourDirectory`* on the C: drive. Linux and macOS file paths have a different format. On my Mac, the path to a file on the desktop is */Users/adebarros/Desktop/*. On Linux, my desktop is located at */home/adebarros/Desktop/*. The directory must exist already; PostgreSQL won't create it for you.

In PostgreSQL, `COPY table_name FROM` is the import function and `COPY table_name TO` is the export function. I'll cover them in depth in Chapter 4; for now, all you need to know is that the `WITH` keyword options ❹ will format the data in the file with each column separated by a *pipe* `|` character. That way, you can easily see where spaces fill out the unused portions of the `char` column.

To see the output, open *typetest.txt* using a plain text editor (not Word or Excel, or another spreadsheet application). The contents should look like this:

```
varchar_column|char_column|text_column
abc|abc       |abc
defghi|defghi    |defghi
```

Even though you specified 10 characters for both the `varchar` and `char` columns, only the `char` column outputs 10 characters every time, padding unused characters with spaces. The `varchar` and `text` columns store only the characters you inserted.

Again, there's no real performance difference among the three types, although this example shows that `char` can potentially consume more storage space than needed. A few unused spaces in each column might seem negligible, but multiply that over millions of rows in dozens of tables and you'll soon wish you had been more economical.

Typically, using `varchar` with an *n* value sufficient to handle outliers is a solid strategy.

Numbers

Number columns hold various types of (you guessed it) numbers, but that's not all: they also allow you to perform calculations on those numbers. That's an important distinction from numbers you store as strings in a character column, which can't be added, multiplied, divided, or perform any other math operation. Also, as I discussed in Chapter 2, numbers stored as characters sort differently than numbers stored as numbers, arranging in text rather than numerical order. So, if you're doing math or the numeric order is important, use number types.

The SQL number types include:

Integers Whole numbers, both positive and negative

Fixed-point and floating-point Two formats of fractions of whole numbers

We'll look at each type separately.

Integers

The integer data type is the most common number type you'll find when exploring data in a SQL database. Think of all the places integers appear in life: your street or apartment number, the serial number on your refrigerator, the number on a raffle ticket. These are *whole numbers*, both positive and negative, including zero.

The SQL standard provides three integer types: `smallint`, `integer`, and `bigint`. The difference between the three types is the maximum size of the numbers they can hold. Table 3-1 shows the upper and lower limits of each, as well as how much storage each requires in bytes.

Table 3-1: Integer Data Types

Name	Storage size	Range
smallint	2 bytes	–32768 to +32767
integer	4 bytes	–2147483648 to +2147483647
bigint	8 bytes	–9223372036854775808 to 9223372036854775807

Even though it eats up the most storage, `bigint` will cover just about any requirement you'll ever have with a number column. Its use is a must if you're working with numbers larger than about 2.1 billion, but you can easily make it your go-to default and never worry. On the other hand, if you're confident numbers will remain within the `integer` limit, that type is a good choice because it doesn't consume as much space as `bigint` (a concern when dealing with millions of data rows).

When the data values will remain constrained, `smallint` makes sense: days of the month or years are good examples. The `smallint` type will use half the storage as `integer`, so it's a smart database design decision if the column values will always fit within its range.

If you try to insert a number into any of these columns that is outside its range, the database will stop the operation and return an `out of range` error.

Auto-Incrementing Integers

In Chapter 1, when you made the `teachers` table, you created an `id` column with the declaration of `serial`: this and its siblings `smallserial` and `bigserial` are not so much true data types as a special *implementation* of the corresponding `smallint`, `integer`, and `bigint` types. When you add a column with a serial type, PostgreSQL will *auto-increment* the value in the column each time you insert a row, starting with 1, up to the maximum of each integer type.

The serial types are implementations of the ANSI SQL standard for auto-numbered *identity columns*. Each database manager implements these in its own way. For example, Microsoft SQL Server uses an `IDENTITY` keyword to set a column to auto-increment.

To use a serial type on a column, declare it in the `CREATE TABLE` statement as you would an integer type. For example, you could create a table called `people` that has an `id` column in each row:

```
CREATE TABLE people (
    id serial,
    person_name varchar(100)
);
```

Every time a new `person_name` is added to the table, the `id` column will increment by 1.

Table 3-2 shows the serial types and the ranges they cover.

Table 3-2: Serial Data Types

Name	Storage size	Range
smallserial	2 bytes	1 to 32767
serial	4 bytes	1 to 2147483647
bigserial	8 bytes	1 to 9223372036854775807

As with this example and in `teachers` in Chapter 1, makers of databases often employ a serial type to create a unique ID number, also known as a key, for each row in the table. Each row then has its own ID that other tables in the database can reference. I'll cover this concept of relating tables in Chapter 6. Because the column is auto-incrementing, you don't need to insert a number into that column when adding data; PostgreSQL handles that for you.

NOTE *Even though a column with a serial type auto-increments each time a row is added, some scenarios will create gaps in the sequence of numbers in the column. If a row is deleted, for example, the value in that row is never replaced. Or, if a row insert is aborted, the sequence for the column will still be incremented.*

Decimal Numbers

As opposed to integers, *decimals* represent a whole number plus a fraction of a whole number; the fraction is represented by digits following a *decimal point*. In a SQL database, they're handled by *fixed-point* and *floating-point* data types. For example, the distance from my house to the nearest grocery store is 6.7 miles; I could insert 6.7 into either a fixed-point or floating-point column with no complaint from PostgreSQL. The only difference is how the computer stores the data. In a moment, you'll see that has important implications.

Fixed-Point Numbers

The fixed-point type is `numeric(`*`precision, scale`*`)`, also called an *arbitrary precision* type. You give the argument `precision` as the maximum number of digits to the left and right of the decimal point, and the argument `scale` as the number of digits allowable on the right of the decimal point. Alternately, you can specify this type using `decimal(`*`precision, scale`*`)`. Both are part of the ANSI SQL standard. If you omit specifying a scale value, the scale will be set to zero; in effect, that creates an integer. If you omit specifying the precision and the scale, the database will store values of any precision and scale up to the maximum allowed. (That's up to 131,072 digits before the decimal point and 16,383 digits after the decimal point, according to the PostgreSQL documentation at *https://www.postgresql.org/docs/current/static/datatype-numeric.html.*)

For example, let's say you're collecting rainfall totals from several local airports—not an unlikely data analysis task. The US National Weather Service provides this data with rainfall typically measured to two decimal places. (And, if you're like me, you have a distant memory of your third-grade math teacher explaining that two digits after a decimal is the hundredths place.)

To record rainfall in the database using five digits total (the precision) and two digits maximum to the right of the decimal (the scale), you'd specify it as `numeric(5,2)`. The database will always return two digits to the right of the decimal point, even if you don't enter a number that contains two digits. For example, 1.47, 1.00, and 121.50.

Floating-Point Types

The two floating-point types are `real` and `double precision`. The difference between the two is how much data they store. The `real` type allows precision to six decimal digits, and `double precision` to 15 decimal points of precision, both of which include the number of digits on both sides of the point. These floating-point types are also called *variable-precision* types. The database stores the number in parts representing the digits and an exponent—the location where the decimal point belongs. So, unlike `numeric`, where we specify fixed precision and scale, the decimal point in a given column can "float" depending on the number.

Using Fixed- and Floating-Point Types

Each type has differing limits on the number of total digits, or precision, it can hold, as shown in Table 3-3.

Table 3-3: Fixed-Point and Floating-Point Data Types

Name	Storage size	Storage type	Range
numeric, decimal	variable	Fixed-point	Up to 131072 digits before the decimal point; up to 16383 digits after the decimal point
real	4 bytes	Floating-point	6 decimal digits precision
double precision	8 bytes	Floating-point	15 decimal digits precision

To see how each of the three data types handles the same numbers, create a small table and insert a variety of test cases, as shown in Listing 3-2:

```
CREATE TABLE number_data_types (
❶   numeric_column numeric(20,5),
    real_column real,
    double_column double precision
);

❷ INSERT INTO number_data_types
VALUES
    (.7, .7, .7),
    (2.13579, 2.13579, 2.13579),
    (2.1357987654, 2.1357987654, 2.1357987654);

SELECT * FROM number_data_types;
```

Listing 3-2: Number data types in action

We've created a table with one column for each of the fractional data types ❶ and loaded three rows into the table ❷. Each row repeats the same number across all three columns. When the last line of the script runs and we select everything from the table, we get the following:

```
numeric_column    real_column    double_column
--------------    -----------    -------------
       0.70000            0.7              0.7
       2.13579        2.13579          2.13579
       2.13580         2.1358     2.1357987654
```

Notice what happened. The `numeric` column, set with a scale of five, stores five digits after the decimal point whether or not you inserted that many. If fewer than five, it pads the rest with zeros. If more than five, it rounds them—as with the third-row number with 10 digits after the decimal.

The `real` and `double precision` columns store only the number of digits present with no padding. Again on the third row, the number is rounded when inserted into the `real` column because that type has a maximum of six digits of precision. The `double precision` column can hold up to 15 digits, so it stores the entire number.

Trouble with Floating-Point Math

If you're thinking, "Well, numbers stored as a floating-point look just like numbers stored as fixed," tread cautiously. The way computers store floating-point numbers can lead to unintended mathematical errors. Look at what happens when we do some calculations on these numbers. Run the script in Listing 3-3:

```
SELECT
❶   numeric_column * 10000000 AS "Fixed",
    real_column  * 10000000 AS "Float"
```

```
FROM number_data_types
❷ WHERE numeric_column = .7;
```

Listing 3-3: Rounding issues with float columns

Here, we multiply the `numeric_column` and the `real_column` by 10 million ❶ and use a `WHERE` clause to filter out just the first row ❷. We should get the same result for both calculations, right? Here's what the query returns:

```
Fixed           Float
-------------   ----------------
7000000.00000   6999999.88079071
```

Hello! No wonder floating-point types are referred to as "inexact." It's a good thing I'm not using this math to launch a mission to Mars or calculate the federal budget deficit.

The reason floating-point math produces such errors is that the computer attempts to squeeze lots of information into a finite number of bits. The topic is the subject of a lot of writings and is beyond the scope of this book, but if you're interested, you'll find a good synopsis at *http://stackoverflow.com/questions/3730019/why-not-use-double-or-float-to-represent-currency/*.

The storage required by the `numeric` data type is variable, and depending on the precision and scale specified, `numeric` can consume considerably more space than the floating-point types. If you're working with millions of rows, it's worth considering whether you can live with relatively inexact floating-point math.

Choosing Your Number Data Type

For now, here are three guidelines to consider when you're dealing with number data types:

1. Use integers when possible. Unless your data uses decimals, stick with integer types.
2. If you're working with decimal data and need calculations to be exact (dealing with money, for example), choose `numeric` or its equivalent, `decimal`. Float types will save space, but the inexactness of floating-point math won't pass muster in many applications. Use them only when exactness is not as important.
3. Choose a big enough number type. Unless you're designing a database to hold millions of rows, err on the side of bigger. When using `numeric` or `decimal`, set the precision large enough to accommodate the number of digits on both sides of the decimal point. With whole numbers, use `bigint` unless you're absolutely sure column values will be constrained to fit into the smaller `integer` or `smallint` types.

Dates and Times

Whenever you enter a date into a search form, you're reaping the benefit of databases having an awareness of the current time (received from the server) plus the ability to handle formats for dates, times, and the nuances of the calendar, such as leap years and time zones. This is essential for storytelling with data, because the issue of *when* something occurred is usually as valuable a question as who, what, or how many were involved.

PostgreSQL's date and time support includes the four major data types shown in Table 3-4.

Table 3-4: Date and Time Data Types

Name	Storage size	Description	Range
timestamp	8 bytes	Date and time	4713 BC to 294276 AD
date	4 bytes	Date (no time)	4713 BC to 5874897 AD
time	8 bytes	Time (no date)	00:00:00 to 24:00:00
interval	16 bytes	Time interval	+/− 178,000,000 years

Here's a rundown of data types for times and dates in PostgreSQL:

timestamp Records date and time, which are useful for a range of situations you might track: departures and arrivals of passenger flights, a schedule of Major League Baseball games, or incidents along a timeline. Typically, you'll want to add the keywords `with time zone` to ensure that the time recorded for an event includes the time zone where it occurred. Otherwise, the timestamp will reflect the time zone setting of your server. The format `timestamp with time zone` is part of the SQL standard; with PostgreSQL you can specify the same data type using `timestamptz`.

date Records just the date.

time Records just the time. Again, you'll want to add the `with time zone` keywords.

interval Holds a value representing a unit of time expressed in the format *`quantity unit`*. It doesn't record the start or end of a time period, only its length. Examples include `12 days` or `8 hours`. (The PostgreSQL documentation at *https://www.postgresql.org/docs/current/static/datatype-datetime.html* lists unit values ranging from `microsecond` to `millennium`.) You'll typically use this type for calculations or filtering on other date and time columns.

Let's focus on the `timestamp with time zone` and `interval` types. To see these in action, run the script in Listing 3-4.

```
❶ CREATE TABLE date_time_types (
      timestamp_column timestamp with time zone,
      interval_column interval
  );
```

```
❷ INSERT INTO date_time_types
  VALUES
      ('2016-12-31 01:00 EST','2 days'),
      ('2016-12-31 01:00 -8','1 month'),
      ('2016-12-31 01:00 Australia/Melbourne','1 century'),
❸     (now(),now(),now(),'1 week');

  SELECT * FROM date_time_types;
```

Listing 3-4: Timestamp and interval types in action

Here, we create a table with a column for both types ❶ and insert four rows ❷. For the first three rows, our insert for the `timestamp_column` uses the same date and time (December 31, 2016 at 1 AM) using the International Organization for Standardization (ISO) format for dates and times: `YYYY-MM-DD hh:mm:ss`. SQL supports additional date formats (such as `MM/DD/YYYY`), but ISO is recommended for portability worldwide.

Following the time, we specify a time zone but use a different format in each of the first three rows: in the first row, we use the abbreviation `EST`, which is Eastern Standard Time in the United States.

In the second row, we set the time zone with the value `-8`. That represents the number of hours difference, or *offset*, from Coordinated Universal Time (UTC). UTC refers to an overall world time standard as well as the value of UTC +/− 00:00, the time zone that covers the United Kingdom and Western Africa. (For a map of UTC timezones, see *https://en.wikipedia.org/wiki/Coordinated_Universal_Time#/media/File:Standard_World_Time_Zones.png*.) Using a value of `-8` specifies a time zone eight hours behind UTC, which is the Pacific Time Zone in the United States and Canada.

For the third row, we specify the time zone using the name of an area and location: `Australia/Melbourne`. That format uses values found in a standard time zone database often employed in computer programming. You can learn more about the time zone database at *https://en.wikipedia.org/wiki/Tz_database*.

In the fourth row, instead of specifying dates, times, and time zones, the script uses PostgreSQL's `now()` function ❸, which captures the current transaction time from your hardware.

After the script runs, the output should look similar to (but not exactly like) this:

```
timestamp_column                interval_column
-----------------------------   ---------------
2016-12-31 01:00:00-05          2 days
2016-12-31 04:00:00-05          1 mon
2016-12-30 09:00:00-05          100 years
2017-01-25 21:31:15.716063-05   7 days
```

Even though we supplied the same date and time in the first three rows on the `timestamp_column`, each row's output differs. The reason is that pgAdmin reports the date and time relative to my time zone, which in the results shown is indicated by the UTC offset of `-05` at the end of each timestamp. A UTC offset of `-05` means five hours behind UTC time, equivalent to the US Eastern Time Zone where I live. If you live in a different time zone, you'll likely see a different offset; the times and dates also may differ from what's shown here. We can change how PostgreSQL reports these timestamp values, and I'll cover how to do that plus other tips for wrangling dates and times in Chapter 11.

Finally, the `interval_column` shows the values you entered. PostgreSQL changed `1 century` to `100 years` and `1 week` to `7 days` because of its preferred default settings for interval display. Read the *Interval Input* section of the PostgreSQL documentation at *https://www.postgresql.org/docs/current/static/datatype-datetime.html* to learn more about options related to intervals.

Using the Interval Data Type in Calculations

Interval data types are useful for easy-to-understand calculations on date and time data. For example, let's say you have a column that holds the date a client signed a contract. Using interval data, you can add 90 days to each contract date to determine when to follow up with the client.

To see how the interval data type works, we'll use the `date_time_types` table we just created, as shown in Listing 3-5:

```
SELECT
    timestamp_column,
    interval_column,
❶   timestamp_column - interval_column AS new_date
FROM date_time_types;
```

Listing 3-5: Using the interval data type

This is a typical `SELECT` statement except we'll compute a column called `new_date` ❶ that contains the result of `timestamp_column` minus `interval_column`. (Computed columns are called *expressions*; we'll use this technique often.) In each row, we subtract the unit of time indicated by the interval data type from the date. This produces the following result:

```
timestamp_column                  interval_column    new_date
-----------------------------     ---------------    -----------------------------
2016-12-31 01:00:00-05            2 days             2016-12-29 01:00:00-05
2016-12-31 04:00:00-05            1 mon              2016-11-30 04:00:00-05
2016-12-30 09:00:00-05            100 years          1916-12-30 09:00:00-05
2017-01-25 21:31:15.716063-05     7 days             2017-01-18 21:31:15.716063-05
```

Note that the `new_date` column by default is formatted as type `timestamp with timezone`, allowing for the display of time values as well as date if the interval value uses them. Again, your output may be different based on your server's time zone.

Miscellaneous Types

The character, number, and date/time types you've learned so far will likely comprise the bulk of the work you do with SQL. But PostgreSQL supports many additional types, including but not limited to:

- A Boolean type that stores a value of `true` or `false`
- Geometric types that include points, lines, circles, and other two-dimensional objects
- Network address types, such as IP or MAC addresses
- A Universally Unique Identifier (UUID) type, sometimes used as a unique key value in tables
- XML and JSON data types that store information in those structured formats

I'll cover these types as required throughout the book.

Transforming Values from One Type to Another with CAST

Occasionally, you may need to transform a value from its stored data type to another type; for example, when you retrieve a number as a character so you can combine it with text or when you must treat a date stored as characters as an actual date type so you can sort it in date order or perform interval calculations. You can perform these conversions using the `CAST()` function.

The `CAST()` function only succeeds when the target data type can accommodate the original value. Casting an integer as text is possible, because the character types can include numbers. Casting text with letters of the alphabet as a number is not.

Listing 3-6 has three examples using the three data type tables we just created. The first two examples work, but the third will try to perform an invalid type conversion so you can see what a type casting error looks like.

```
❶ SELECT timestamp_column, CAST(timestamp_column AS varchar(10))
  FROM date_time_types;

❷ SELECT numeric_column,
         CAST(numeric_column AS integer),
         CAST(numeric_column AS varchar(6))
  FROM number_data_types;

❸ SELECT CAST(char_column AS integer) FROM char_data_types;
```

Listing 3-6: Three `CAST()` examples

The first `SELECT` statement ❶ returns the `timestamp_column` value as a `varchar`, which you'll recall is a variable-length character column. In this case, I've set the character length to 10, which means when converted to a character string, only the first 10 characters are kept. That's handy in this case, because that just gives us the date segment of the column and excludes the time. Of course, there are better ways to remove the time from a timestamp, and I'll cover those in Chapter 11.

The second `SELECT` statement ❷ returns the `numeric_column` three times: in its original form and then as an integer and as a character. Upon conversion to an integer, PostgreSQL rounds the value to a whole number. But with the `varchar` conversion, no rounding occurs: the value is simply sliced at the sixth character.

The final `SELECT` doesn't work ❸: it returns an error of `invalid input syntax for integer` because letters can't become integers!

It's always best when you write SQL that can be read by another person who might pick it up later, and the way `CAST()` is written makes it fairly obvious what you intended when you used it. However, PostgreSQL also offers a less-obvious shortcut notation that takes less space: the *double colon*.

Insert the double colon in between the name of the column and the data type you want to convert it to. For example, these two statements cast `timestamp_column` as a `varchar`:

```
SELECT timestamp_column, CAST(timestamp_column AS varchar(10))
FROM date_time_types;

SELECT timestamp_column::varchar(10)
FROM date_time_types;
```

Use whichever suits you, but be aware that the double colon is a PostgreSQL-only implementation not found in other SQL variants.

Wrapping Up

You're now equipped to better understand the nuances of the data formats you encounter while digging into databases. If you come across monetary values stored as floating-point numbers, you'll be sure to convert them to decimals before performing any math. And you'll know how to use the right kind of text column to keep your database from growing too big.

Next, I'll continue with SQL foundations and show you how to import external data into your database.

Try It Yourself

Continue exploring data types with these exercises:

1. Your company delivers fruit and vegetables to local grocery stores, and you need to track the mileage driven by each driver each day to a tenth of a mile. Assuming no driver would ever travel more than 999 miles in a day, what would be an appropriate data type for the mileage column in your table? Why?

2. In the table listing each driver in your company, what are appropriate data types for the drivers' first and last names? Why is it a good idea to separate first and last names into two columns rather than having one larger name column?
3. Assume you have a text column that includes strings formatted as dates. One of the strings is written as `'4//2017'`. What will happen when you try to convert that string to the `timestamp` data type?

4

IMPORTING AND EXPORTING DATA

So far, you've learned how to add a handful of rows to a table using SQL `INSERT` statements. A row-by-row insert is useful for making quick test tables or adding a few rows to an existing table. But it's more likely you'll need to load hundreds, thousands, or even millions of rows, and no one wants to write separate `INSERT` statements in those situations. Fortunately, you don't have to.

If your data exists in a *delimited* plaintext file (with one table row per line of text and each column value separated by a comma or other character) PostgreSQL can import the data in bulk via its `COPY` command. This command is a PostgreSQL-specific implementation with options for including or excluding columns and handling various delimited text types.

In the opposite direction, `COPY` will also *export* data from PostgreSQL tables or from the result of a query to a delimited plaintext file. This technique is handy when you want to share data with colleagues or move it into another format, such as an Excel file.

I briefly touched on `COPY` for export in "Characters" on page 24, but in this chapter I'll discuss import and export in more depth. For importing, I'll start by introducing you to one of my favorite data sets: the Decennial U.S. Census population tally by county.

Three steps form the outline of most of the imports you'll do:

1. Prep the source data in the form of a delimited text file.
2. Create a table to store the data.
3. Write a `COPY` script to perform the import.

After the import is done, we'll check the data and look at additional options for importing and exporting.

A delimited text file is the most common file format that's portable across proprietary and open source systems, so we'll focus on that file type. If you want to transfer data from another database program's proprietary format directly to PostgreSQL, such as Microsoft Access or MySQL, you'll need to use a third-party tool. Check the PostgreSQL wiki at *https://wiki.postgresql.org/wiki/* and search for "Converting from other Databases to PostgreSQL" for a list of tools.

If you're using SQL with another database manager, check the other database's documentation for how it handles bulk imports. The MySQL database, for example, has a `LOAD DATA INFILE` statement, and Microsoft's SQL Server has its own `BULK INSERT` command.

Working with Delimited Text Files

Many software applications store data in a unique format, and translating one data format to another is about as easy as a person trying to read the Cyrillic alphabet if they understand only English. Fortunately, most software can import from and export to a delimited text file, which is a common data format that serves as a middle ground.

A delimited text file contains rows of data, and each row represents one row in a table. In each row, a character separates, or delimits, each data column. I've seen all kinds of characters used as delimiters, from ampersands to pipes, but the comma is most commonly used; hence the name of a file type you'll see often: *comma-separated values (CSV)*. The terms CSV and comma-delimited are interchangeable.

Here's a typical data row you might see in a comma-delimited file:

```
John,Doe,123 Main St.,Hyde Park,NY,845-555-1212
```

Notice that a comma separates each piece of data—first name, last name, street, town, state, and phone—without any spaces. The commas tell the software to treat each item as a separate column, either upon import or export. Simple enough.

Quoting Columns that Contain Delimiters

Using commas as a column delimiter leads to a potential dilemma: what if the value in a column includes a comma? For example, sometimes people combine an apartment number with a street address, as in 123 Main St., Apartment 200. Unless the system for delimiting accounts for that extra comma, during import the line will appear to have an extra column and cause the import to fail.

To handle such cases, delimited files wrap columns that contain a delimiter character with an arbitrary character called a *text qualifier* that tells SQL to ignore the delimiter character held within. Most of the time in comma-delimited files the text qualifier used is the double quote. Here's the example data row again, but with the street name surrounded by double quotes:

```
John,Doe,"123 Main St., Apartment 200",Hyde Park,NY,845-555-1212
```

On import, the database will recognize that double quotes signify one field regardless of whether it finds a delimiter within the quotes. When importing CSV files, PostgreSQL by default ignores delimiters inside double quoted columns, but you can specify a different text qualifier if your import requires it. (And, given the sometimes odd choices made by IT professionals, you may indeed need to employ a different character.)

Handling Header Rows

Another feature you'll often find inside a delimited text file is the *header row*. As the name implies, it's a single row at the top, or head, of the file that lists the name of each data field. Usually, a header is created during the export of data from a database. Here's an example with the delimited row I've been using:

```
FIRSTNAME,LASTNAME,STREET,CITY,STATE,PHONE
John,Doe,"123 Main St., Apartment 200",Hyde Park,NY,845-555-1212
```

Header rows serve a few purposes. For one, the values in the header row identify the data in each column, which is particularly useful when you're deciphering a file's contents. Second, some database managers (although not PostgreSQL) use the header row to map columns in the delimited file to the correct columns in the import table. Because PostgreSQL doesn't use the header row, we don't want that row imported to a table, so we'll use a `HEADER` option in the `COPY` command to exclude it. I'll cover this with all `COPY` options in the next section.

Using COPY to Import Data

To import data from an external file into our database, first we need to check out a source CSV file and build the table in PostgreSQL to hold the data. Thereafter, the SQL for the import is relatively simple. All you need are the three lines of code in Listing 4-1:

```
❶ COPY table_name
❷ FROM 'C:\YourDirectory\your_file.csv'
❸ WITH (FORMAT CSV, HEADER);
```

Listing 4-1: Using `COPY` *for data import*

The block of code starts with the `COPY` keyword ❶ followed by the name of the target table, which must already exist in your database. Think of this syntax as meaning, "Copy data to my table called *`table_name`*."

The `FROM` keyword ❷ identifies the full path to the source file, including its name. The way you designate the path depends on your operating system. For Windows, begin with the drive letter, colon, backslash, and directory names. For example, to import a file located on my Windows desktop, the `FROM` line would read:

```
FROM 'C:\Users\Anthony\Desktop\my_file.csv'
```

On macOS or Linux, start at the system root directory with a forward slash and proceed from there. Here's what the `FROM` line might look like when importing a file located on my Mac desktop:

```
FROM '/Users/anthony/Desktop/my_file.csv'
```

Note that in both cases the full path and filename are surrounded by single quotes. For the examples in the book, I use the Windows-style path *`C:\YourDirectory\`* as a placeholder. Replace that with the path where you stored the file.

The `WITH` keyword ❸ lets you specify options, surrounded by parentheses, that you can tailor to your input or output file. Here we specify that the external file should be comma-delimited, and that we should exclude the file's header row in the import. It's worth examining all the options in the official PostgreSQL documentation at *https://www.postgresql.org/docs/current/static/sql-copy.html*, but here is a list of the options you'll commonly use:

Input and output file format

Use the `FORMAT` *`format_name`* option to specify the type of file you're reading or writing. Format names are `CSV`, `TEXT`, or `BINARY`. Unless you're deep into building technical systems, you'll rarely encounter a need to work with `BINARY`, where data is stored as a sequence of bytes. More often, you'll work with standard CSV files. In the `TEXT` format, a *tab* character is the delimiter by default (although you can specify another character) and backslash characters such as `\r` are recognized as their ASCII equivalents—in this case, a carriage return. It's used mainly by PostgreSQL's built-in backup programs.

Presence of a header row

On import, use `HEADER` to specify that the source file has a header row. You an also specify it longhand as `HEADER ON`, which tells the database to start importing with the second line of the file, preventing the unwanted import of the header. You don't want the column names in the header to become part of the data in the table. On export, using `HEADER` tells the database to include the column names as a header row in the output file, which is usually helpful to do.

Delimiter

The `DELIMITER '`*`character`*`'` option lets you specify which character your import or export file uses as a delimiter. The delimiter must be a single character and cannot be a carriage return. If you use `FORMAT CSV`, the assumed delimiter is a comma. I include `DELIMITER` here to show that you have the option to specify a different delimiter if that's how your data arrived. For example, if you received pipe-delimited data, you would treat the option this way: `DELIMITER '|'`.

Quote character

Earlier, you learned that in a CSV, commas inside a single column value will mess up your import unless the column value is surrounded by a character that serves as a text qualifier, telling the database to handle the value within as one column. By default, PostgreSQL uses the double quote, but if the CSV you're importing uses a different character, you can specify it with the `QUOTE '`*`quote_character`*`'` option.

Now that you better understand delimited files, you're ready to import one.

Importing Census Data Describing Counties

The data set you'll work with in this import exercise is considerably larger than the `teachers` table you made in Chapter 1. It contains census data about every county in the United States and is 3,143 rows deep and 91 columns wide.

To understand the data, it helps to know a little about the U.S. Census. Every 10 years, the government conducts a full count of the population—one of several ongoing programs by the Census Bureau to collect demographic data. Each household in America receives a questionnaire about each person in it—their age, gender, race, and whether they are Hispanic or not. The U.S. Constitution mandates the count to determine how many members from each state make up the U.S. House of Representatives. Based on the 2010 Census, for example, Texas gained four seats in the House while New York and Ohio lost two seats each. Although apportioning House seats is the count's main purpose, the data's also a boon for trend trackers studying the population. A good synopsis of the 2010 count's findings is available at *https://www.census.gov/prod/cen2010/briefs/c2010br-01.pdf*.

The Census Bureau reports overall population totals and counts by race and ethnicity for various geographies including states, counties, cities, places, and school districts. For this exercise, I compiled a select collection of columns for the 2010 Census county-level counts into a file named *us_counties_2010.csv*. Download the *us_counties_2010.csv* file from *https://www.nostarch.com/practicalSQL/* and save it to a folder on your computer.

Open the file with a plaintext editor. You should see a header row that begins with these columns:

```
NAME,STUSAB,SUMLEV,REGION,DIVISION,STATE,COUNTY --snip--
```

Let's explore some of the columns by examining the code for creating the import table.

Creating the us_counties_2010 Table

The code in Listing 4-2 shows only an abbreviated version of the `CREATE TABLE` script; many of the columns have been omitted. The full version is available (and annotated) along with all the code examples in the book's resources. To import it properly, you'll need to download the full table definition.

```
CREATE TABLE us_counties_2010 (
❶ geo_name varchar(90),
❷ state_us_abbreviation varchar(2),
❸ summary_level varchar(3),
❹ region smallint,
  division smallint,
  state_fips varchar(2),
  county_fips varchar(3),
❺ area_land bigint,
  area_water bigint,
❻ population_count_100_percent integer,
  housing_unit_count_100_percent integer,
❼ internal_point_lat numeric(10,7),
  internal_point_lon numeric(10,7),
❽ p0010001 integer,
  p0010002 integer,
  p0010003 integer,
  p0010004 integer,
  p0010005 integer,
  --snip--
  p0040049 integer,
  p0040065 integer,
```

```
    p0040072 integer,
    h0010001 integer,
    h0010002 integer,
    h0010003 integer
);
```

Listing 4-2: A `CREATE TABLE` *statement for census county data*

To create the table, in pgAdmin click on the `analysis` database that you created in Chapter 1. (It's best to store the data in this book in `analysis` because we'll reuse some of it in later chapters.) Select the **Query Tool** from the menu bar to open it. Paste the script into the window and run it.

Return to the main pgAdmin window, and in the object browser, right-click and refresh the `analysis` database. Choose **Schemas ▸ Public ▸ Tables** to see the new table. Although it's empty, you can see the structure by running a basic `SELECT` in pgAdmin's Query Tool:

```
SELECT * from us_counties_2010;
```

When you run the `SELECT` query, you'll see the columns in the table you created. No data rows exist yet.

Census Columns and Data Types

Before we import the CSV file into the table, let's walk through several of the columns and the data types I chose in Listing 4-2. As my guide, I used the official census data dictionary for this data set found at *http://www.census.gov/prod/cen2010/doc/pl94-171.pdf*, although I give some columns more readable names in the table definition. Relying on a data dictionary when possible is good practice, because it helps you avoid misconfiguring columns or potentially losing data. Always ask if one is available, or do an online search if the data is public.

In this set of census data, and thus the table you just made, each row describes the demographics of one county, starting with its `geo_name` ❶ and its two-character state abbreviation, the `state_us_abbreviation` ❷. Because both are text, we store them as `varchar`. The data dictionary indicates that the maximum length of the `geo_name` field is 90 characters, but because most names are shorter, using `varchar` will conserve space if we fill the field with a shorter name, such as `Lee County`, while allowing us to specify the maximum 90 characters.

The geography, or summary level, represented by each row is described by `summary_level` ❸. We're only working with county-level data, so the code is the same for each row: `050`. Even though that code resembles a number, we're treating it as text by again using `varchar`. If we used an integer type, that leading `0` would be stripped on import, leaving `50`. We don't want to do that because `050` is the complete summary level code, and we'd be altering the meaning of the data if the leading `0` were lost. Also, we won't be doing any math with this value.

Numbers from 0 to 9 in `region` and `division` ❹ represent the location of a county in the United States, such as the Northeast, Midwest, or South Atlantic. No number is higher than 9, so we define the columns with type `smallint`. We again use `varchar` for `state_fips` and `county_fips`, which are the standard federal codes for those entities, and those codes contain leading zeros that should not be stripped. It's always important to distinguish codes from numbers; these state and county values are actually labels as opposed to numbers used for math.

The number of square meters for land and water, respectively, in the county are recorded in `area_land` and `area_water` ❺. In certain places—such as Alaska, where there's lots of land to go with all that snow—some values easily surpass the maximum of 2,147,483,648 the `integer` type provides. For that reason, we're using `bigint`, which will handle the 376,855,656,455 square meters in the Yukon-Koyukuk Census Area with room to spare.

Next, `population_count_100_percent` and `housing_unit_count_100_percent` ❻ are the total counts of population and housing units in the geography. In 2010, the United States had 308.7 million people and 131.7 million housing units. The population and housing units for any county fits well within the `integer` data type's limits, so we use that for both.

The *latitude* and *longitude* of a point near the center of the county, called an internal point, are specified in `internal_point_lat` and `internal_point_lon` ❼, respectively. The Census Bureau—along with many mapping systems—expresses latitude and longitude coordinates using a *decimal degrees* system. Latitude represents positions north and south on the globe, with the equator at 0 degrees, the North Pole at 90 degrees, and the South Pole at –90 degrees.

Longitude represents locations east and west, with the *Prime Meridian* that passes through Greenwich in London at 0 degrees longitude. From there, longitude increases both east and west (positive numbers to the east and negative to the west) until they meet at 180 degrees on the opposite side of the globe. The location there, known as the *antimeridian*, is used as the basis for the *International Date Line*.

When reporting interior points, the Census Bureau uses up to seven decimal places. With a value up to 180 to the left of the decimal, we need to account for a maximum of 10 digits total. So, we're using `numeric` with a precision of `10` and a scale of `7`.

NOTE *PostgreSQL includes a geometric data type called* `point` *that can represent latitude and longitude in a single column. We'll explore it when we cover geographical queries later in the book.*

Finally, we reach a series of columns ❽ that contain iterations of the population counts by race and ethnicity for the county as well as housing unit counts. The full set of 2010 Census data contains 291 of these columns. I've pared that down to 78 for this exercise, omitting many of the columns to make the data set more compact for these exercises.

I won't discuss all the columns now, but Table 4-1 shows a small sample.

Table 4-1: Census Population-Count Columns

Column name	Description
p0010001	Total population
p0010002	Population of one race
p0010003	Population of one race: White alone
p0010004	Population of one race: Black or African American alone
p0010005	Population of one race: American Indian and Alaska Native alone
p0010006	Population of one race: Asian alone
p0010007	Population of one race: Native Hawaiian and Other Pacific Islander alone
p0010008	Population of one race: Some Other Race alone

You'll explore this data more in the next chapter when we look at math with SQL. For now, let's run the import.

Performing the Census Import with COPY

Now you're ready to bring the census data into the table. Run the code in Listing 4-3, remembering to change the path to the file to match the location of the data on your computer:

```
COPY us_counties_2010
FROM 'C:\YourDirectory\us_counties_2010.csv'
WITH (FORMAT CSV, HEADER);
```

Listing 4-3: Importing census data using `COPY`

When the code executes, you should see the following message in pgAdmin:

```
Query returned successfully: 3143 rows affected
```

That's good news: the import CSV has the same number of rows. If you have an issue with the source CSV or your import statement, the database will throw an error. For example, if one of the rows in the CSV had more columns than in the target table, you'd see an error message that provides a hint as to how to fix it:

```
ERROR: extra data after last expected column
SQL state: 22P04
Context: COPY us_counties_2010, line 2: "Autauga County,AL,050,3,6,01,001 ..."
```

Even if no errors are reported, it's always a good idea to visually scan the data you just imported to ensure everything looks as expected. Start with a `SELECT` of all columns and rows:

```
SELECT * FROM us_counties_2010;
```

There should be 3,143 rows displayed in pgAdmin, and as you scroll left and right through the result set, each field should have the expected values. Let's review some columns that we took particular care to define with the appropriate data types. For example, run the following query to show the counties with the largest `area_land` values. We'll use a `LIMIT` clause, which will cause the query to only return the number of rows we want; here, we'll ask for three:

```
SELECT geo_name, state_us_abbreviation, area_land
FROM us_counties_2010
ORDER BY area_land DESC
LIMIT 3;
```

This SQL ranks county-level geographies from largest land area to smallest in square meters. We defined `area_land` as `bigint` because the largest values in the field are bigger than the upper range provided by regular `integer`. As you might expect, big Alaskan geographies are at the top:

```
geo_name                    state_us_abbreviation    area_land
-------------------------   ---------------------    ------------
Yukon-Koyukuk Census Area   AK                       376855656455
North Slope Borough         AK                       229720054439
Bethel Census Area          AK                       105075822708
```

Next, check the latitude and longitude columns of `internal_point_lat` and `internal_point_lon`, which we defined with `numeric(10,7)`. This code sorts the counties by longitude from the greatest to smallest value. This time, we'll use `LIMIT` to retrieve five rows:

```
SELECT geo_name, state_us_abbreviation, internal_point_lon
FROM us_counties_2010
ORDER BY internal_point_lon DESC
LIMIT 5;
```

Longitude measures locations from east to west, with locations west of the Prime Meridian in England represented as negative numbers starting with –1, –2, –3, and so on the farther west you go. We sorted in descending order, so we'd expect the easternmost counties of the United States to show at the top of the query result. Instead—surprise!—there's a lone Alaska geography at the top:

```
geo_name                     state_us_abbreviation    internal_point_lon
--------------------------   ---------------------    ------------------
Aleutians West Census Area   AK                              178.3388130
Washington County            ME                              -67.6093542
Hancock County               ME                              -68.3707034
Aroostook County             ME                              -68.6494098
Penobscot County             ME                              -68.6574869
```

Here's why: the Alaskan Aleutian Islands extend so far west (farther west than Hawaii) that they cross the antimeridian at 180 degrees longitude by less than 2 degrees. Once past the antimeridian, longitude turns positive, counting back down to 0. Fortunately, it's not a mistake in the data; however, it's a fact you can tuck away for your next trivia team competition.

Congratulations! You have a legitimate set of government demographic data in your database. I'll use it to demonstrate exporting data with `COPY` later in this chapter, and then you'll use it to learn math functions in Chapter 5. Before we move on to exporting data, let's examine a few additional importing techniques.

Importing a Subset of Columns with COPY

If a CSV file doesn't have data for all the columns in your target database table, you can still import the data you have by specifying which columns are present in the data. Consider this scenario: you're researching the salaries of all town supervisors in your state so you can analyze government spending trends by geography. To get started, you create a table called `supervisor_salaries` with the code in Listing 4-4:

```
CREATE TABLE supervisor_salaries (
    town varchar(30),
    county varchar(30),
    supervisor varchar(30),
    start_date date,
    salary money,
    benefits money
);
```

Listing 4-4: Creating a table to track supervisor salaries

You want columns for the town and county, the supervisor's name, the date he or she started, and salary and benefits (assuming you just care about current levels). However, the first county clerk you contact says, "Sorry, we only have town, supervisor, and salary. You'll need to get the rest from elsewhere." You tell them to send a CSV anyway. You'll import what you can.

I've included such a sample CSV you can download in the book's resources at *https://www.nostarch.com/practicalSQL/*, called *supervisor_salaries.csv*. You could try to import it using this basic `COPY` syntax:

```
COPY supervisor_salaries
FROM 'C:\YourDirectory\supervisor_salaries.csv'
WITH (FORMAT CSV, HEADER);
```

But if you do, PostgreSQL will return an error:

```
********** Error **********
ERROR: missing data for column "start_date"
SQL state: 22P04
Context: COPY supervisor_salaries, line 2: "Anytown,Jones,27000"
```

The database complains that when it got to the fourth column of the table, `start_date`, it couldn't find any data in the CSV. The workaround for this situation is to tell the database which columns in the table are present in the CSV, as shown in Listing 4-5:

```
COPY supervisor_salaries ❶(town, supervisor, salary)
FROM 'C:\YourDirectory\supervisor_salaries.csv'
WITH (FORMAT CSV, HEADER);
```

Listing 4-5: Importing salaries data from CSV to three table columns

By noting in parentheses ❶ the three present columns after the table name, we tell PostgreSQL to only look for data to fill those columns when it reads the CSV. Now, if you select the first couple of rows from the table, you'll see only those columns filled:

```
town          county    supervisor    start_date    salary        benefits
----------    ------    ----------    ----------    ----------    --------
Anytown                 Jones                       $27,000.00
Bumblyburg              Baker                       $24,999.00
```

Add a Default Value to a Column During Import

What if you want to populate the `county` column during the import, even though the value is missing from the CSV file? You can do so by using a *temporary table*. Temporary tables exist only until you end your database session. When you reopen the database, those tables disappear (so if you lose your connection to the database, you also need to re-create them). They're handy for performing intermediary operations on data as part of your processing pipeline; we'll use one to add a county name to the `supervisor_salaries` table as we import the CSV.

Start by clearing the data you already imported into `supervisor_salaries` using a `DELETE` query:

```
DELETE FROM supervisor_salaries;
```

When that query finishes, run the code in Listing 4-6:

```
❶ CREATE TEMPORARY TABLE supervisor_salaries_temp (LIKE supervisor_salaries);

❷ COPY supervisor_salaries_temp (town, supervisor, salary)
  FROM 'C:\YourDirectory\supervisor_salaries.csv'
  WITH (FORMAT CSV, HEADER);

❸ INSERT INTO supervisor_salaries (town, county, supervisor, salary)
  SELECT town, 'Some County', supervisor, salary
  FROM supervisor_salaries_temp;
```

```
❹ DROP TABLE supervisor_salaries_temp;
```

Listing 4-6: Use a temporary table to add a default value to a column during import

This script performs four tasks. First, we create a temporary table called `supervisor_salaries_temp` ❶ based on the original `supervisor_salaries` table by passing as an argument the `LIKE` keyword (covered in Chapter 2) followed by the parent table to copy. Then we import the *supervisor_salaries.csv* file ❷ into the temporary table using the now-familiar `COPY` syntax.

Next, we use an `INSERT` statement to fill the salaries table ❸. Instead of specifying values, we employ a `SELECT` statement to query the temporary table. That query specifies the value for the second column, not as a column name, but as a string inside single quotes.

Finally, we use `DROP TABLE` to erase the temporary table ❹. The temporary table will automatically disappear when you disconnect from the PostgreSQL session, but this removes it now in case we want to run the query again against another CSV.

After you run the query, `SELECT` the first couple of rows to see the effect:

```
town         county        supervisor   start_date   salary       benefits
----------   -----------   ----------   ----------   ----------   --------
Anytown      Some County   Jones                     $27,000.00
Bumblyburg   Some County   Baker                     $24,999.00
```

Now you've filled the `county` field with a value. The path to this import might seem laborious, but it's instructive to see how data processing can require multiple steps to get the desired results. The good news is that this temporary table demo is an apt indicator of the flexibility SQL offers to control data handling.

Using COPY to Export Data

The main difference between exporting and importing data with `COPY` is that rather than using `FROM` to identify the source data, you use `TO` for the path and name of the output file. You control how much data to export—an entire table, just a few columns, or to fine-tune it even more, the results of a query.

Let's look at three quick examples.

Exporting All Data

The simplest export sends everything in a table to a file. Earlier, you created the table `us_counties_2010` with 91 columns and 3,143 rows of census data. The SQL in Listing 4-7 exports all the data to a text file named *us_counties_export .txt*. The `WITH` keyword option tells PostgreSQL to include a header row and use the pipe symbol instead of a comma for a delimiter. I've used the *.txt* file extension here for two reasons. First, it demonstrates that you can export to any text file format; second, we're using a pipe for a delimiter, not a comma. I like to avoid calling files a CSV unless they truly have commas as a separator.

Remember to change the output directory to your preferred location.

```
COPY us_counties_2010
TO 'C:\YourDirectory\us_counties_export.txt'
WITH (FORMAT CSV, HEADER, DELIMITER '|')
```

Listing 4-7: Exporting an entire table with `COPY`

Exporting Particular Columns

You don't always need (or want) to export all your data: you might have sensitive information, such as Social Security numbers or birthdates, that need to remain private. Or, in the case of the census county data, maybe you're working with a mapping program and only need the county name and its geographic coordinates to plot the locations. We can export only these three columns by listing them in parentheses after the table name, as shown in Listing 4-8. Of course, you must enter these column names precisely as they're listed in the data for PostgreSQL to recognize them.

```
COPY us_counties_2010 (geo_name, internal_point_lat, internal_point_lon)
TO 'C:\YourDirectory\us_counties_latlon_export.txt'
WITH (FORMAT CSV, HEADER, DELIMITER '|')
```

Listing 4-8: Exporting selected columns from a table with `COPY`

Exporting Query Results

Additionally, you can add a query to `COPY` to fine-tune your output. In Listing 4-9 we export the name and state abbreviation of only those counties whose name contains the letters `mill` in either uppercase or lowercase by using the case-insensitive `ILIKE` and the `%` wildcard character we covered in "Using `LIKE` and `ILIKE` with `WHERE`" on page 19.

```
COPY (
    SELECT geo_name, state_us_abbreviation
    FROM us_counties_2010
    WHERE geo_name ILIKE '%mill%'
     )
TO 'C:\YourDirectory\us_counties_mill_export.txt'
WITH (FORMAT CSV, HEADER, DELIMITER '|')
```

Listing 4-9: Exporting query results with `COPY`

After running the code, your output file should have nine rows with county names including Miller, Roger Mills, and Vermillion.

Import and Export Through pgAdmin

At times, the SQL `COPY` commands won't be able to handle certain imports and exports, typically when you're connected to a PostgreSQL instance running on a computer other than yours, perhaps elsewhere on a network. When that happens, you might not have access to that computer's filesystem, which makes setting the path in the `FROM` or `TO` clause difficult.

One workaround is to use pgAdmin's built-in import/export wizard. In pgAdmin's object browser (the left vertical pane), locate the list of tables in your `analysis` database by choosing **Databases ▸ analysis ▸ Schemas ▸ public ▸ Tables**.

Next, right-click on the table you want to import to or export from, and select **Import/Export**. A dialog appears that lets you choose either to import or export from that table, as shown in Figure 4-1.

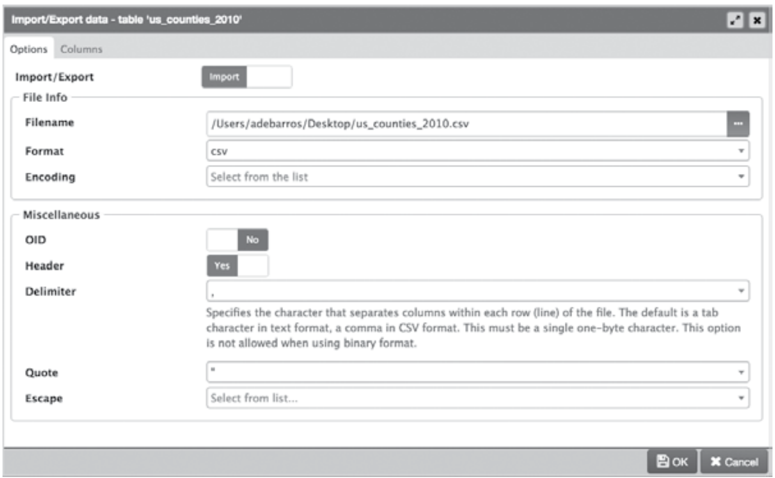


Figure 4-1: The pgAdmin Import/Export dialog

To import, move the **Import/Export** slider to Import. Then click the three dots to the right of the **Filename** box to locate your CSV file. From the **Format** drop-down list, choose CSV. Then adjust the header, delimiter, quoting, and other options as needed. Click **OK** to import the data.

To export, use the same dialog and follow similar steps.

Wrapping Up

Now that you've learned how to bring external data into your database, you can start digging into a myriad of data sets, whether you want to explore one of the thousands of publicly available data sets, or data related to your own career or studies. Plenty of data is available in CSV format or a format easily convertible to CSV. Look for data dictionaries to help you understand the data and choose the right data type for each field.

The census data you imported as part of this chapter's exercises will play a starring role in the next chapter in which we explore math functions with SQL.

Try It Yourself

Continue your exploration of data import and export with these exercises. Remember to consult the PostgreSQL documentation at *https://www.postgresql.org/docs/current/static/sql-copy.html* for hints:

1. Write a `WITH` statement to include with `COPY` to handle the import of an imaginary text file whose first couple of rows look like this:

```
id:movie:actor
50:#Mission: Impossible#:Tom Cruise
```

2. Using the table `us_counties_2010` you created and filled in this chapter, export to a CSV file the 20 counties in the United States that have the most housing units. Make sure you export only each county's name, state, and number of housing units.

HINT *Housing units are totaled for each county in the column* `housing_unit_count_100_percent`.

3. Imagine you're importing a file that contains a field with these values:

```
17519.668
20084.461
18976.335
```

4. Will a column in your target table with data type `numeric(3,8)` work for these values? Why or why not?

5

BASIC MATH AND STATS WITH SQL

If your data includes any of the number data types we explored in Chapter 3—integers, decimals, or floating points—sooner or later your analysis will include some calculations. For example, you might want to know the average of all the dollar values in a column, or add values in two columns to produce a total for each row. SQL handles calculations ranging from basic math through advanced statistics.

In this chapter, I'll start with the basics and progress to math functions and beginning statistics. I'll also discuss calculations related to percentages and percent change. For several of the exercises, we'll use the 2010 Decennial Census data you imported in Chapter 4.

Math Operators

Let's start with the basic math you learned in grade school (and all's forgiven if you've forgotten some of it). Table 5-1 shows nine math operators you'll use most often in your calculations. The first four (addition, subtraction, multiplication, and division) are part of the ANSI SQL standard that are implemented in all database systems. The others are PostgreSQL-specific operators, although if you're using another database, it likely has functions or operators to perform those operations. For example, the modulo operator `%` works in Microsoft SQL Server and MySQL as well as with PostgreSQL. If you're using another database system, check its documentation.

Table 5-1: Basic Math Operators

Operator	Description
+	Addition
-	Subtraction
*	Multiplication
/	Division (returns the quotient only, no remainder)
%	Modulo (returns just the remainder)
^	Exponentiation
|/	Square root
||/	Cube root
!	Factorial

We'll step through each of these operators by executing simple SQL queries on plain numbers rather than operating on a table or another database object. You can either enter the statements separately into the pgAdmin query tool and execute them one at a time, or if you copied the code for this chapter from the resources at *https://www.nostarch.com/practicalSQL/*, you can highlight each line before executing it.

Math and Data Types

As you work through the examples, note the data type of each result, which is listed beneath each column name in the pgAdmin results grid. The type returned for a calculation will vary depending on the operation and the data type of the input numbers.

In calculations with an operator between two numbers—addition, subtraction, multiplication, and division—the data type returned follows this pattern:

- Two integers return an `integer`.
- A `numeric` on either side of the operator returns a `numeric`.
- Anything with a floating-point number returns a floating-point number of type `double precision`.

However, the exponentiation, root, and factorial functions are different. Each takes one number either before or after the operator and returns numeric and floating-point types, even when the input is an integer.

Sometimes the result's data type will suit your needs; other times, you may need to use `CAST` to change the data type, as mentioned in Chapter 3, such as if you need to feed the result into a function that takes a certain type. I'll note those times as we work through the book.

Adding, Subtracting, and Multiplying

Let's start with simple integer addition, subtraction, and multiplication. Listing 5-1 shows three examples, each with the `SELECT` keyword followed by the math formula. Since Chapter 2, we've used `SELECT` for its main purpose: to retrieve data from a table. But with PostgreSQL, Microsoft's SQL Server, MySQL, and some other database management systems, it's possible to omit the table name for math and string operations while testing, as we do here. For readability's sake, I recommend you use a single space before and after the math operator; although using spaces isn't strictly necessary for your code to work, it is good practice.

```
❶ SELECT 2 + 2;
❷ SELECT 9 - 1;
❸ SELECT 3 * 4;
```

Listing 5-1: Basic addition, subtraction, and multiplication with SQL

None of these statements are rocket science, so you shouldn't be surprised that running `SELECT 2 + 2;` ❶ in the query tool shows a result of `4`. Similarly, the examples for subtraction ❷ and multiplication ❸ yield what you'd expect: `8` and `12`. The output displays in a column, as with any query result. But because we're not querying a table and specifying a column, the results appear beneath a `?column?` name, signifying an unknown column:

```
?column?
--------
       4
```

That's okay. We're not affecting any data in a table, just displaying a result.

Division and Modulo

Division with SQL gets a little trickier because of the difference between math with integers and math with decimals, which was mentioned earlier. Add in *modulo*, an operator that returns just the *remainder* in a division operation, and the results can be confusing. So, to make it clear, Listing 5-2 shows four examples:

```
❶ SELECT 11 / 6;
❷ SELECT 11 % 6;
```

```
❸ SELECT 11.0 / 6;
❹ SELECT CAST (11 AS numeric(3,1)) / 6;
```

Listing 5-2: Integer and decimal division with SQL

The first statement uses the `/` operator ❶ to divide the integer `11` by another integer, `6`. If you do that math in your head, you know the answer is `1` with a remainder of `5`. However, running this query yields `1`, which is how SQL handles division of one integer by another—by reporting only the integer *quotient*. If you want to retrieve the *remainder* as an integer, you must perform the same calculation using the modulo operator `%`, as in ❷. That statement returns just the remainder, in this case `5`. No single operation will provide you with both the quotient and the remainder as integers.

Modulo is useful for more than just fetching a remainder: you can also use it as a test condition. For example, to check whether a number is even, you can test it using the `% 2` operation. If the result is `0` with no remainder, the number is even.

If you want to divide two numbers and have the result return as a `numeric` type, you can do so in two ways: first, if one or both of the numbers is a `numeric`, the result will by default be expressed as a `numeric`. That's what happens when I divide `11.0` by `6` ❸. Execute that query, and the result is `1.83333`. The number of decimal digits displayed may vary according to your PostgreSQL and system settings.

Second, if you're working with data stored only as integers and need to force decimal division, you can use an approach mentioned in Chapter 3 and `CAST` one of the integers to a `numeric` type ❹. Executing this again returns `1.83333`.

Exponents, Roots, and Factorials

Beyond the basics, PostgreSQL-flavored SQL also provides operators to square, cube, or otherwise raise a base number to an exponent, as well as find roots or the factorial of a number. Listing 5-3 shows these operations in action:

```
❶ SELECT 3 ^ 4;
❷ SELECT |/ 10;
  SELECT sqrt(10);
❸ SELECT ||/ 10;
❹ SELECT 4 !;
```

Listing 5-3: Exponents, roots, and factorials with SQL

The exponentiation operator `^` allows you to raise a given base number to an exponent, as in ❶, where `3 ^ 4` (colloquially, we'd call that three to the fourth power) returns `81`.

You can find the square root of a number in two ways: using the `|/` operator ❷ or the `sqrt(n)` function. For a cube root, use the `||/` operator ❸. Both are *prefix operators*, named because they come before a single value.

To find the *factorial* of a number, use the `!` operator. It's a *suffix operator*, coming after a single value. You'll use factorials in many places in math, but perhaps the most common is to determine how many ways a number of items can be ordered. Say you have four photographs. How many ways could you order them next to each other on a wall? To find the answer, you'd calculate the factorial by starting with the number of items and multiplying all the smaller positive integers. So, in ❹, the factorial statement of `4 !` is equivalent to 4 × 3 × 2 × 1. That's 24 ways to order four photos. No wonder decorating takes so long sometimes!

Again, these operators are specific to PostgreSQL; they're not part of the SQL standard. If you're using another database application, check its documentation for how it implements these operations.

Minding the Order of Operations

Can you recall from your earliest math lessons what the order of operations, or *operator precedence*, is on a mathematical expression? When you string together several numbers and operators, which calculations does SQL execute first? Not surprisingly, SQL follows the established math standard. For the PostgreSQL operators discussed so far, the order is:

1. Exponents and roots
2. Multiplication, division, modulo
3. Addition and subtraction

Given these rules, you'll need to encase an operation in parentheses if you want to calculate it in a different order. For example, the following two expressions yield different results:

```
SELECT 7 + 8 * 9;
SELECT (7 + 8) * 9;
```

The first expression returns `79` because the multiplication operation receives precedence and is processed before the addition. The second returns `135` because the parentheses force the addition operation to occur first.

Here's a second example using exponents:

```
SELECT 3 ^ 3 - 1;
SELECT 3 ^ (3 - 1);
```

Exponent operations take precedence over subtraction, so without parentheses the entire expression is evaluated left to right and the operation to find 3 to the power of 3 happens first. Then 1 is subtracted, returning `26`. In the second example, the parentheses force the subtraction to happen first, so the operation results in `9`, which is 3 to the power of 2.

Keep operator precedence in mind to avoid having to correct your analysis later!

Doing Math Across Census Table Columns

Let's try to use the most frequently used SQL math operators on real data by digging into the 2010 Decennial Census population table, `us_counties_2010`, that you imported in Chapter 4. Instead of using numbers in queries, we'll use the names of the columns that contain the numbers. When we execute the query, the calculation will occur on each row of the table.

To refresh your memory about the data, run the script in Listing 5-4. It should return 3,143 rows showing the name and state of each county in the United States, and the number of people who identified with one of six race categories or a combination of two or more races.

The 2010 Census form received by each household—the so-called "short form"—allowed people to check either just one or multiple boxes under the question of race. (You can review the form at *https://www.census.gov/2010census/pdf/2010_Questionnaire_Info.pdf*.) People who checked one box were counted in categories such as "White Alone" or "Black or African American Alone." Respondents who selected more than one box were tabulated in the overall category of "Two or More Races," and the census data set breaks those down in detail.

```
SELECT geo_name,
       state_us_abbreviation AS "st",
       p0010001 ❶AS "Total Population",
       p0010003 AS "White Alone",
       p0010004 AS "Black or African American Alone",
       p0010005 AS "Am Indian/Alaska Native Alone",
       p0010006 AS "Asian Alone",
       p0010007 AS "Native Hawaiian and Other Pacific Islander Alone",
       p0010008 AS "Some Other Race Alone",
       p0010009 AS "Two or More Races"
FROM us_counties_2010;
```

Listing 5-4: Selecting census population columns by race with aliases

In `us_counties_2010`, each race and household data column contains a census code. For example, the "Asian Alone" column is reported as `p0010006`. Although those codes might be economical and compact, they make it difficult to understand which column is which when the query returns with just that code. In Listing 5-4, I employ a little trick to clarify the output by using the `AS` keyword ❶ to give each column a more readable alias in the result set. We could rename all the columns upon import, but with the census it's best to use the code to refer to the same column names in the documentation if needed.

Adding and Subtracting Columns

Now, let's try a simple calculation on two of the race columns in Listing 5-5, adding the number of people who identified as white alone or black alone in each county.

```
SELECT geo_name,
       state_us_abbreviation AS "st",
       p0010003 AS "White Alone",
       p0010004 AS "Black Alone",
❶      p0010003 + p0010004 AS "Total White and Black"
FROM us_counties_2010;
```

Listing 5-5: Adding two columns in us_counties_2010

Providing `p0010003 + p0010004` ❶ as one of the columns in the `SELECT` statement handles the calculation. Again, I use the `AS` keyword to provide a readable alias for the column. If you don't provide an alias, PostgreSQL uses the label `?column?`, which is far less than helpful.

Run the query to see the results. The first few rows should resemble this output:

```
geo_name          st    White Alone    Black Alone    Total White and Black
--------------    --    -----------    -----------    ---------------------
Autauga County    AL          42855           9643                    52498
Baldwin County    AL         156153          17105                   173258
Barbour County    AL          13180          12875                    26055
```

A quick check with a calculator or pencil and paper confirms that the total column equals the sum of the columns you added. Excellent!

Now, let's build on this to test our data and validate that we imported columns correctly. The six race "Alone" columns plus the "Two or More Races" column should add up to the same number as the total population. The code in Listing 5-6 should show that it does:

```
SELECT geo_name,
       state_us_abbreviation AS "st",
     ❶ p0010001 AS "Total",
     ❷ p0010003 + p0010004 + p0010005 + p0010006 + p0010007
           + p0010008 + p0010009 AS "All Races",
     ❸ (p0010003 + p0010004 + p0010005 + p0010006 + p0010007
           + p0010008 + p0010009) - p0010001 AS "Difference"
FROM us_counties_2010
❹ ORDER BY "Difference" DESC;
```

Listing 5-6: Check census data totals

This query includes the population total ❶, followed by a calculation adding the seven race columns as `All Races` ❷. The population total and the races total should be identical, but rather than manually check, we also add a column that subtracts the population total column from the sum of the race columns ❸. That column, named `Difference`, should contain a zero in each row if all the data is in the right place. To avoid having to scan all 3,143 rows, we add an `ORDER BY` clause ❹ on the named column. Any rows showing a difference should appear at the top or bottom of the query result.

Run the query; the first few rows should provide this result:

```
geo_name          st     Total      All Races     Difference
--------------    --     ------     ---------     ----------
Autauga County    AL      54571         54571              0
Baldwin County    AL     182265        182265              0
Barbour County    AL      27457         27457              0
```

With the `Difference` column showing zeros, we can be confident that our import was clean. Whenever I encounter or import a new data set, I like to perform little tests like this. They help me better understand the data and head off any potential issues before I dig into analysis.

Finding Percentages of the Whole

Let's dig deeper into the census data to find meaningful differences in the population demographics of the counties. One way to do this (with any data set, in fact) is to calculate what percentage of the whole a particular variable represents. With the census data, we can learn a lot by comparing percentages from county to county and also by examining how percentages vary over time.

To figure out the percentage of the whole, divide the number in question by the total. For example, if you had a basket of 12 apples and used nine in a pie, that would be 9 / 12 or .75—commonly expressed as 75%.

To try this on the census counties data, use the code in Listing 5-7, which calculates for each county the percentage of the population that reported its race as Asian:

```
SELECT geo_name,
       state_us_abbreviation AS "st",
❶      (CAST (p0010006 AS DECIMAL(8,1)) / p0010001) * 100 AS "pct_asian"
FROM us_counties_2010
ORDER BY "pct_asian" DESC;
```

Listing 5-7: Calculating the percent of the population that is Asian by county

The key piece of this query divides `p0010006`, the column with the count of Asian alone, by `p0010001`, the column for total population ❶.

If we use the data as their original integer types, we won't get the fractional result we need: every row will display a result of 0, the quotient. Instead, we force decimal division by using `CAST` on one of the integers. The last part multiplies the result by 100 to present the result as a fraction of 100—the way most people understand percentages.

By sorting from highest to lowest percentage, the top of the output is as follows:

```
geo_name                      st     Pct Asian
--------------------------    --     -----------------------
Honolulu County               HI     43.89497769109962474000
Aleutians East Borough        AK     35.97580388411333970100
San Francisco County          CA     33.27165361664607226500
```

```
Santa Clara County           CA     32.02237037519322063600
Kauai County                 HI     31.32461880132953749400
Aleutians West Census Area   AK     28.87969789606185937800
```

Tracking Percent Change

Another key indicator in data analysis is percent change: how much bigger, or smaller, is one number than another? Percent change calculations are often employed when analyzing change over time, and they're particularly useful for comparing change among similar items.

Some examples include:

- The year-over-year change in the number of vehicles sold by each automobile maker.
- The monthly change in subscriptions to each email list owned by a marketing firm.
- The annual increase or decrease in enrollment at schools across the nation.

The formula to calculate percent change can be expressed like this:

```
(New Number - Old Number) / Old Number
```

So, if you own a lemonade stand and sold 73 glasses of lemonade today and 59 glasses yesterday, you'd figure the day-to-day percent change like this:

```
(73 - 59) / 59 = .237 = 23.7%
```

Let's try this with a small collection of test data related to spending in departments of a hypothetical local government. Listing 5-8 calculates which departments had the greatest percentage increase and loss:

```
❶ CREATE TABLE percent_change (
      department varchar(20),
      spend_2014 numeric(10,2),
      spend_2017 numeric(10,2)
  );

❷ INSERT INTO percent_change
  VALUES
      ('Building', 250000, 289000),
      ('Assessor', 178556, 179500),
      ('Library', 87777, 90001),
      ('Clerk', 451980, 650000),
      ('Police', 250000, 223000),
      ('Recreation', 199000, 195000);

  SELECT department,
         spend_2014,
         spend_2017,
```

```
   ❸ round( (spend_2017 - spend_2014) /
                    spend_2014 * 100, 1) AS "pct_change"
FROM percent_change;
```

Listing 5-8: Calculating percent change

Listing 5-8 creates a small table called `percent_change` ❶ and inserts six rows ❷ with data on department spending for the years 2014 and 2017. The percent change formula ❸ subtracts `spend_2014` from `spend_2017` and then divides by `spend_2014`. We multiply by 100 to express the result as a portion of 100.

To simplify the output, this time I've added the `round()` function to remove all but one decimal place. The function takes two arguments: the column or expression to be rounded, and the number of decimal places to display. Because both numbers are type `numeric`, the result will also be a `numeric`.

The script creates this result:

```
department    spend_2014    spend_2017    pct_change
----------    ----------    ----------    ----------
Building       250000.00     289000.00          15.6
Assessor       178556.00     179500.00           0.5
Library         87777.00      90001.00           2.5
Clerk          451980.00     650000.00          43.8
Police         250000.00     223000.00         -10.8
Recreation     199000.00     195000.00          -2.0
```

Now, it's just a matter of finding out why the Clerk's department spending has outpaced others in the town.

Aggregate Functions for Average and Sums

So far, we've performed math operations across columns in each row of a table. SQL also lets you calculate a result from values within the same column using *aggregate functions*. You can see a full list of PostgreSQL aggregates, which calculate a single result from multiple inputs, at *https://www.postgresql.org/docs/current/static/functions-aggregate.html*. Two of the most-used aggregate functions in data analysis are `avg()` and `sum()`.

Returning to the `us_counties_2010` census table, it's reasonable to want to calculate the total population of all counties plus the average population of all counties. Using `avg()` and `sum()` on column `p0010001` (the total population) makes it easy, as shown in Listing 5-9. Again, we use the `round()` function to remove numbers after the decimal point in the average calculation.

```
SELECT sum(p0010001) AS "County Sum",
       round(avg(p0010001), 0) AS "County Average"
FROM us_counties_2010;
```

Listing 5-9: Using `sum()` and `avg()` aggregate functions

This calculation produces the following result:

```
County Sum     County Average
----------     --------------
 308745538              98233
```

The population for all counties in the United States in 2010 added up to approximately 308.7 million, and the average county population was 98,233.

Finding the Median

The *median* value in a set of numbers is as important an indicator, if not more so, than the average. Here's the difference between median and average, and why median matters:

Average The sum of all the values divided by the number of values

Median The "middle" value in an ordered set of values

Why is median important for data analysis? Consider this example: let's say six kids ages 10, 11, 10, 9, 13, and 12 go on a field trip. It's easy to add the ages and divide by six to get the group's average age:

```
(10 + 11 + 10 + 9 + 13 + 12) / 6 = 10.8
```

Because the ages are within a narrow range, the 10.8 average is a good representation of the group. But averages are less helpful when the values are bunched, or skewed, toward one end of the distribution, or if the group includes outliers.

For example, what if an older chaperone joins the field trip? With ages of 10, 11, 10, 9, 13, 12, and 46, the average age increases considerably:

```
(10 + 11 + 10 + 9 + 13 + 12 + 46) / 7 = 15.9
```

Now the average doesn't represent the group well because the outlier skews it, making it an unreliable indicator.

This is where medians shine. The median is the midpoint in an ordered list of values—the point at which half the values are more and half are less. Using the field trip, we order the attendees' ages from lowest to highest:

```
9, 10, 10, 11, 12, 13, 46
```

The middle (median) value is 11. Half the values are higher, and half are lower. Given this group, the median of 11 is a better picture of the typical age than the average of 15.9.

If the set of values is an even number, you average the two middle numbers to find the median. Let's add another student to the field trip:

```
9, 10, 10, 11, 12, 12, 13, 46
```

Now, the two middle values are 11 and 12. To find the median, we average them: 11.5.

Medians are reported frequently in financial news. Reports on housing prices often use medians because a few sales of McMansions in a ZIP code that is otherwise modest can make averages useless. The same goes for sports player salaries: one or two superstars can skew a team's average.

A good test is to calculate the average and the median for a group of values. If they're close, the group is probably normally distributed (the familiar bell curve), and the average is useful. If they're far apart, the values are not normally distributed and the median is the better representation.

Percentile Functions for Median

PostgreSQL (as with most relational databases) does not have a built-in `median()` function, similar to what you'd find in Excel or other spreadsheet programs. It's also not included in the ANSI SQL standard. But we can use a SQL *percentile* function to find the median as well as other *quantiles* or *cut points*, which are the points that divide a group of numbers into equal sizes. Percentile functions are part of standard ANSI SQL.

In statistics, percentiles indicate the point in an ordered set of data below which a certain percentage of the data is found. For example, a doctor might tell you that your height places you in the 60th percentile for an adult in your age group. That means 60% of people are your height or shorter.

The median is equivalent to the 50th percentile—again, half the values are below and half above. SQL's percentile functions allow us to calculate that easily, although we have to pay attention to a difference in how the two versions of the function—`percentile_cont(n)` and `percentile_disc(n)`—handle calculations. Both functions are part of the ANSI SQL standard and are present in PostgreSQL, Microsoft SQL Server, and other databases.

The `percentile_cont(n)` function calculates percentiles as *continuous* values. That is, the result does not have to be one of the numbers in the data set but can be a decimal value in between two of the numbers. This follows the methodology for calculating medians on an even number of values, where the median is the average of the two middle numbers. On the other hand, `percentile_disc(n)` returns only *discrete* values. That is, the result returned will be rounded to one of the numbers in the set.

To make this distinction clear, let's use Listing 5-10 to make a test table and fill in six numbers.

```
CREATE TABLE percentile_test (
    numbers integer
);

INSERT INTO percentile_test (numbers) VALUES
    (1), (2), (3), (4), (5), (6);

SELECT
  ❶ percentile_cont(.5)
    WITHIN GROUP (ORDER BY numbers),
  ❷ percentile_disc(.5)
```

```
    WITHIN GROUP (ORDER BY numbers)
FROM percentile_test;
```

Listing 5-10: Testing SQL percentile functions

In both the continuous ❶ and discrete ❷ percentile functions, we enter `.5` to represent the 50th percentile, same as the median. Running the code returns the following:

```
percentile_cont    percentile_disc
---------------    ---------------
            3.5                  3
```

The `percentile_cont()` function returned what we'd expect the median to be: 3.5. But because `percentile_disc()` calculates discrete values, it reports 3, the last value in the first 50% of the numbers. Because the accepted method of calculating medians is to average the two middle values in an even-numbered set, use `percentile_cont(.5)` to find a median.

Median and Percentiles with Census Data

Our Census data can show how a median tells a different story than an average. Listing 5-11 adds `percentile_cont()` alongside the `sum()` and `avg()` aggregates we've used so far:

```
SELECT sum(p0010001) AS "County Sum",
       round(avg(p0010001), 0) AS "County Average",
       percentile_cont(.5)
       WITHIN GROUP (ORDER BY p0010001) AS "County Median"
FROM us_counties_2010;
```

Listing 5-11: Using `sum()`, `avg()`, and `percentile_cont()` aggregate functions

Your result should equal the following:

```
County Sum    County Average    County Median
----------    --------------    -------------
 308745538             98233            25857
```

The median and average are far apart, which shows that averages can mislead. As of 2010, half the counties in America had fewer than 25,857 people, whereas half had more. If you gave a presentation on U.S. demographics and told the audience that the "average county in America had 98,200 people," they'd walk away with a skewed picture of reality. Nearly 40 counties had a million or more people as of the 2010 Decennial Census, and Los Angeles County had close to 10 million. That pushes the average higher.

Percentile Functions for Other Quantiles

You can also slice data into smaller equal groups. Most common are *quartiles* (four equal groups), *quintiles* (five groups), and *deciles* (10 groups). To find any individual value, you can just plug it into a percentile function. For example, to find the value marking the first quartile, or the lowest 25% of data, you'd use a value of `.25`:

```
percentile_cont(.25)
```

However, entering values one at a time is laborious if you want to generate multiple cut points. Instead, you can pass values into `percentile_cont()` using an *array*, a SQL data type that contains a list of items. Listing 5-12 shows how to calculate all four quartiles at once:

```
SELECT percentile_cont(❶array[.25,.5,.75])
       WITHIN GROUP (ORDER BY p0010001)
FROM us_counties_2010;
```

Listing 5-12: Passing an array of values to `percentile_cont()`

In this example, we create an array of cut points by enclosing values in a *constructor* ❶ called `array[]`. Inside the square brackets, we provide comma-separated values representing the three points at which to cut to create four quartiles. Run the query, and you should see this output:

```
quartiles
---------------------
{11104.5,25857,66699}
```

Because we passed in an array, PostgreSQL returns an array, denoted by curly brackets. Each quartile is separated by commas. The first quartile is 11,104.5, which means 25% of counties have a population that is equal to or lower than this value. The second quartile is the same as the median: 25,857. The third quartile is 66,699, meaning the largest 25% of counties have at least this large of a population.

Arrays come with a host of functions (noted for PostgreSQL at *https://www.postgresql.org/docs/current/static/functions-array.html*) that allow you to perform tasks such as adding or removing values or counting the elements. A handy function for working with the result returned in Listing 5-12 is `unnest()`, which makes the array easier to read by turning it into rows. Listing 5-13 shows the code:

```
SELECT unnest(
            percentile_cont(array[.25,.5,.75])
            WITHIN GROUP (ORDER BY p0010001)
            ) AS "quartiles"
FROM us_counties_2010;
```

Listing 5-13: Using `unnest()` *to turn an array into rows*

Now the output should be in rows:

```
quartiles
---------
  11104.5
    25857
    66699
```

If we were computing deciles, pulling them from the resulting array and displaying them in rows would be especially helpful.

Creating a median() Function

Although PostgreSQL does not have a built-in `median()` aggregate function, if you're adventurous, the PostgreSQL wiki at *http://wiki.postgresql.org/wiki/Aggregate_Median* provides a script to create one. Listing 5-14 shows the script:

```
❶ CREATE OR REPLACE FUNCTION _final_median(anyarray)
     RETURNS float8 AS
  $$
    WITH q AS
    (
       SELECT val
       FROM unnest($1) val
       WHERE VAL IS NOT NULL
       ORDER BY 1
    ),
    cnt AS
    (
      SELECT COUNT(*) AS c FROM q
    )
    SELECT AVG(val)::float8
    FROM
    (
      SELECT val FROM q
      LIMIT  2 - MOD((SELECT c FROM cnt), 2)
      OFFSET GREATEST(CEIL((SELECT c FROM cnt) / 2.0) - 1,0)
    ) q2;
  $$
  LANGUAGE sql IMMUTABLE;

❷ CREATE AGGREGATE median(anyelement) (
    SFUNC=array_append,
    STYPE=anyarray,
    FINALFUNC=_final_median,
    INITCOND='{}'
  );
```

Listing 5-14: Creating a `median()` aggregate function in PostgreSQL

Given what you've learned so far, the SQL for making a `median()` aggregate function may look inscrutable. I'll cover functions in more depth later in the book, but for now note that the code contains two main blocks: one to make a function called `_final_median` ❶ that sorts the values in the column and finds the midpoint, and a second that serves as the callable aggregate function `median()` ❷ and passes values to `_final_median`. For now, you can skip reviewing the script line by line and simply execute the code.

Let's add the `median()` function to the census query and try it next to `percentile_cont()`, as shown in Listing 5-15:

```
SELECT sum(p0010001) AS "County Sum",
       round(AVG(p0010001), 0) AS "County Average",
       median(p0010001) AS "County Median",
       percentile_cont(.5)
       WITHIN GROUP (ORDER BY p0010001) AS "50th Percentile"
FROM us_counties_2010;
```

Listing 5-15: Using a `median()` *aggregate function*

The query results show that the median function and the percentile function return the same value:

```
County Sum     County Average     County Median     50th Percentile
----------     --------------     -------------     ---------------
 308745538              98233             25857               25857
```

So when should you use `median()` instead of a percentile function? There is no simple answer. The `median()` syntax is easier to remember, albeit a chore to set up for each database, and it's specific to PostgreSQL. Also, in practice, `median()` executes more slowly and may perform poorly on large data sets or slow machines. On the other hand, `percentile_cont()` is portable across several SQL database managers, including Microsoft SQL Server, and allows you to find any percentile from 0 to 100. Ultimately, you can try both and decide.

Finding the Mode

Additionally, we can find the *mode*, the value that appears most often, using the PostgreSQL `mode()` function. The function is not part of standard SQL and has a syntax similar to the percentile functions. Listing 5-16 shows a `mode()` calculation on `p0010001`, the total population column:

```
SELECT mode() WITHIN GROUP (ORDER BY p0010001)
FROM us_counties_2010;
```

Listing 5-16: Finding the most frequent value with `mode()`

The result is `21720`, a population count shared by counties in Mississippi, Oregon, and West Virginia.

Wrapping Up

Working with numbers is a key step in acquiring meaning from your data, and with the math skills covered in this chapter, you're ready to handle the foundations of numerical analysis with SQL. Later in the book, you'll learn about deeper statistical concepts including regression and correlation. At this point, you have the basics of sums, averages, and percentiles. You've also learned how a median can be a fairer assessment of a group of values than an average. That alone can help you avoid inaccurate conclusions.

In the next chapter, I'll introduce you to the power of joining data in two or more tables to increase your options for data analysis. We'll use the 2010 Census data you've already loaded into the `analysis` database and explore additional data sets.

Try It Yourself

Here are three exercises to test your SQL math skills:

1. Write a SQL statement for calculating the area of a circle whose radius is 5 inches. (If you don't remember the formula, it's an easy web search.) Do you need parentheses in your calculation? Why or why not?
2. Using the 2010 Census county data, find which New York state county has the highest percentage of the population that identified as "American Indian/Alaska Native Alone." What can you learn about that county from online research that explains the relatively large proportion of American Indian population compared with other New York counties?
3. Was the 2010 median county population higher in California or New York?

6

JOINING TABLES IN A RELATIONAL DATABASE

In Chapter 1, I introduced the concept of a *relational database*, an application that supports data stored across multiple, related tables. In a relational model, each table typically holds data on one entity—such as students, cars, purchases, houses—and each row in the table describes one of those entities. A process known as a *table join* allows us to link rows in one table to rows in other tables.

The concept of relational databases came from the British computer scientist Edgar F. Codd. While working for IBM in 1970, he published a paper called "A Relational Model of Data for Large Shared Data Banks." His ideas revolutionized database design and led to the development of SQL. Using the relational model, you can build tables that eliminate duplicate data, are easier to maintain, and provide for increased flexibility in writing queries to get just the data you want.

Linking Tables Using JOIN

To connect tables in a query, we use a `JOIN ... ON` statement (or one of the other `JOIN` variants I'll cover in this chapter). The `JOIN` statement links one table to another in the database during a query, using matching values in columns we specify in both tables. The syntax takes this form:

```
SELECT *
FROM table_a JOIN table_b
ON table_a.key_column = table_b.foreign_key_column
```

This is similar to the basic `SELECT` syntax you've already learned, but instead of naming one table in the `FROM` clause, we name a table, give the `JOIN` keyword, and then name a second table. The `ON` keyword follows, where we specify the columns we want to use to match values. When the query runs, it examines both tables and then returns columns from both tables where the values match in the columns specified in the `ON` clause.

Matching based on equality between values is the most common use of the `ON` clause, but you can use any expression that evaluates to the *Boolean* results `true` or `false`. For example, you could match where values from one column are greater than or equal to values in the other:

```
ON table_a.key_column >= table_b.foreign_key_column
```

That's rare, but it's an option if your analysis requires it.

Relating Tables with Key Columns

Consider this example of relating tables with key columns: imagine you're a data analyst with the task of checking on a public agency's payroll spending by department. You file a Freedom of Information Act request for that agency's salary data, expecting to receive a simple spreadsheet listing each employee and their salary, arranged like this:

```
dept    location    first_name    last_name    salary
----    --------    ----------    ---------    ------
Tax     Atlanta     Nancy         Jones        62500
Tax     Atlanta     Lee           Smith        59300
IT      Boston      Soo           Nguyen       83000
IT      Boston      Janet         King         95000
```

But that's not what arrives. Instead, the agency sends you a data dump from its payroll system: a dozen CSV files, each representing one table in its database. You read the document explaining the data layout (be sure to always ask for it!) and start to make sense of the columns in each table. Two of the tables stand out: one named `employees` and another named `departments`.

Using the code in Listing 6-1, let's create versions of these tables, insert rows, and examine how to join the data in both tables. Using the `analysis` database you've created for these exercises, run all the code, and then look at the data either by using a basic SELECT statement or clicking on the table name in pgAdmin and selecting **View Data ▸ View All Rows**.

```
CREATE TABLE departments (
    dept_id bigserial,
    dept varchar(100),
    city varchar(100),
 ❶ CONSTRAINT dept_key PRIMARY KEY (dept_id),
 ❷ CONSTRAINT dept_city_unique UNIQUE (dept, city)
);

CREATE TABLE employees (
    emp_id bigserial,
    first_name varchar(100),
    last_name varchar(100),
    salary integer,
 ❸ dept_id integer REFERENCES departments (dept_id),
 ❹ CONSTRAINT emp_key PRIMARY KEY (emp_id),
 ❺ CONSTRAINT emp_dept_unique UNIQUE (emp_id, dept_id)
);

INSERT INTO departments (dept, city)
VALUES
    ('Tax', 'Atlanta'),
    ('IT', 'Boston');

INSERT INTO employees (first_name, last_name, salary, dept_id)
VALUES
    ('Nancy', 'Jones', 62500, 1),
    ('Lee', 'Smith', 59300, 1),
    ('Soo', 'Nguyen', 83000, 2),
    ('Janet', 'King', 95000, 2);
```

Listing 6-1: Creating the departments *and* employees *tables*

The two tables follow Codd's relational model in that each describes attributes about a single entity, in this case the agency's departments and employees. In the departments table, you should see the following contents:

```
dept_id    dept    city
-------    ----    -------
      1    Tax     Atlanta
      2    IT      Boston
```

The dept_id column is the table's primary key. A primary key is a column or collection of columns whose values uniquely identify each row in a table. A valid primary key column enforces certain constraints:

- The column or collection of columns must have a unique value for each row.
- The column or collection of columns can't have missing values.

You define the primary key for departments ❶ and employees ❹ using a CONSTRAINT keyword, which I'll cover in depth with additional constraint types in Chapter 7. The dept_id column uniquely identifies the department, and although this example contains only a department name and city, such a table would likely include additional information, such as an address or contact information.

The employees table should have the following contents:

```
emp_id    first_name    last_name    salary    dept_id
------    ----------    ---------    ------    -------
     1    Nancy         Jones        62500           1
     2    Lee           Smith        59300           1
     3    Soo           Nguyen       83000           2
     4    Janet         King         95000           2
```

The emp_id column uniquely identifies each row in the employees table. For you to know which department each employee works in, the table includes a dept_id column. The values in this column refer to values in the departments table's primary key. We call this a *foreign key*, which you add as a constraint ❸ when creating the table. A foreign key constraint requires a value entered in a column to already exist in the primary key of the table it references. So, values in dept_id in the employees table must exist in dept_id in the departments table; otherwise, you can't add them. Unlike a primary key, a foreign key column can be empty, and it can contain duplicate values.

In this example, the dept_id associated with the employee Nancy Jones is 1; this refers to the value of 1 in the departments table's primary key, dept_id. That tells us that Nancy Jones is part of the Tax department located in Atlanta.

NOTE *Primary key values only need to be unique within a table. That's why it's okay for both the* employees *table and the* departments *table to have primary key values using the same numbers.*

Both tables also include a UNIQUE constraint, which I'll also discuss in more depth in Chapter 7. Briefly, it guarantees that values in a column, or a combination of values in more than one column, are unique. In departments, it requires that each row have a unique pair of values for dept and city ❷. In employees, each row must have a unique pair of emp_id and dept_id ❺. You add these constraints to avoid duplicate data. For example, you can't have two tax departments in Atlanta.

You might ask: what is the advantage of breaking apart data into components like this? Well, consider what this sample of data would look like if you had received it the way you initially thought you would, all in one table:

```
dept    location    first_name    last_name    salary
----    --------    ----------    ---------    ------
Tax     Atlanta     Nancy         Jones        62500
Tax     Atlanta     Lee           Smith        59300
IT      Boston      Soo           Nguyen       83000
IT      Boston      Janet         King         95000
```

First, when you combine data from various entities in one table, inevitably you have to repeat information. This happens here: the department name and location is spelled out for each employee. This is fine when the table consists of four rows like this, or even 4,000. But when a table holds millions of rows, repeating lengthy strings is redundant and wastes precious space. Second, cramming unrelated data into one table makes managing the data difficult. What if the Marketing department changes its name to Brand Marketing? Each row in the table would require an update. It's simpler to store department names and locations in just one table and update it only once.

Now that you know the basics of how tables can relate, let's look at how to join them in a query.

Querying Multiple Tables Using JOIN

When you join tables in a query, the database connects rows in both tables where the columns you specified for the join have matching values. The query results then include columns from both tables if you requested them as part of the query. You also can use columns from the joined tables to filter results using a `WHERE` clause.

Queries that join tables are similar in syntax to basic `SELECT` statements. The difference is that the query also specifies the following:

- The tables and columns to join, using a SQL `JOIN ... ON` statement
- The type of join to perform using variations of the `JOIN` keyword

Let's look at the overall `JOIN ... ON` syntax first and then explore various types of joins. To join the example `employees` and `departments` tables and get the name of the department for each employee, start by writing a query like the one in Listing 6-2:

```
❶ SELECT *
❷ FROM employees JOIN departments
❸ ON employees.dept_id = departments.dept_id;
```

Listing 6-2: Joining the `employees` and `departments` tables

In the example, you include an asterisk wildcard with the `SELECT` statement to choose all columns from both tables ❶. Next, the `JOIN` keyword ❷ comes between the two tables you want data from. Finally, you specify the columns to join the tables using the `ON` keyword. For each table, you provide the table name, a period, and the column that contains the key values. An equal sign goes between the two table-column names ❸.

When you run the query, the results include all values from both tables where values in the dept_id columns match. In fact, even the dept_id field appears twice because you selected all columns of both tables:

```
emp_id   first_name   last_name   salary   dept_id   dept_id   dept   city
------   ----------   ---------   ------   -------   -------   ----   -------
     1   Nancy        Jones        62500         1         1   Tax    Atlanta
     2   Lee          Smith        59300         1         1   Tax    Atlanta
     3   Soo          Nguyen       83000         2         2   IT     Boston
     4   Janet        King         95000         2         2   IT     Boston
```

So, even though the data lives in two tables, each with a focused set of columns, you can query those tables to pull the relevant data back together. Later, in "SELECT Specific Columns in a JOIN" on page 85 I'll show you how to retrieve only the columns you want from both tables.

JOIN Types

There's more than one way to join tables in SQL, and the type of join you'll use depends on how you want to retrieve data. The following list describes the different types of joins. While reviewing each, it's helpful to think of two tables side by side, one on the left of the JOIN keyword and the other on the right. A data-driven example of each join follows the list:

JOIN Returns rows from both tables where matching values are found in the joined columns of both tables. Alternate syntax is INNER JOIN.

LEFT JOIN Returns every row from the left table plus rows that match values in the joined column from the right table. When a left table row doesn't have a match in the right table, the result shows no values from the right table.

RIGHT JOIN Returns every row from the right table plus rows that match the key values in the key column from the left table. When a right table row doesn't have a match in the left table, the result shows no values from the left table.

FULL OUTER JOIN Returns every row from both tables and matches rows; then joins the rows where values in the joined columns match. If there's no match for a value in either the left or right table, the query result contains an empty row for the other table.

CROSS JOIN Returns every possible combination of rows from both tables.

These join types are best illustrated with data. Imagine you have two simple tables that hold names of schools. To better visualize join types, let's call the tables schools_left and schools_right. There are four rows in schools_left:

```
id   left_school
--   ------------------------
 1   Oak Street School
 2   Roosevelt High School
 5   Washington Middle School
 6   Jefferson High School
```

There are five rows in `schools_right`:

```
id   right_school
--   --------------------
 1   Oak Street School
 2   Roosevelt High School
 3   Morrison Elementary
 4   Chase Magnet Academy
 6   Jefferson High School
```

Notice that only schools with the `id` of `1`, `2`, and `6` match in both tables. Working with two tables of similar data is a common scenario for a data analyst, and a common task would be to identify which schools exist in both tables. Using different joins can help you find those schools plus other details.

Again using your `analysis` database, run the code in Listing 6-3 to build and populate these two tables:

```
CREATE TABLE schools_left (
 ❶ id integer CONSTRAINT left_id_key PRIMARY KEY,
    left_school varchar(30)
);

CREATE TABLE schools_right (
 ❷ id integer CONSTRAINT right_id_key PRIMARY KEY,
    right_school varchar(30)
);

❸ INSERT INTO schools_left (id, left_school) VALUES
    (1, 'Oak Street School'),
    (2, 'Roosevelt High School'),
    (5, 'Washington Middle School'),
    (6, 'Jefferson High School');

INSERT INTO schools_right (id, right_school) VALUES
    (1, 'Oak Street School'),
    (2, 'Roosevelt High School'),
    (3, 'Morrison Elementary'),
    (4, 'Chase Magnet Academy'),
    (6, 'Jefferson High School');
```

Listing 6-3: Creating two tables to explore `JOIN` types

We create and fill two tables: the declarations for these should by now look familiar, but there's one new element: we add a primary key to each table. After the declaration for the `schools_left` `id` column ❶ and `schools_right` `id` column, ❷ the keywords `CONSTRAINT` *`key_name`* `PRIMARY KEY` indicate that those columns will serve as the primary key for their table. That means for each row in both tables, the `id` column must be filled and contain a value that is unique for each row in that table. Finally, we use the familiar `INSERT` statements ❸ to add the data to the tables.

JOIN

We use a JOIN, or INNER JOIN, when we want to return rows that have a match in the columns we used for the join. To see an example of this, run the code in Listing 6-4, which joins the two tables you just made:

```
SELECT *
FROM schools_left JOIN schools_right
ON schools_left.id = schools_right.id;
```

Listing 6-4: Using JOIN

Similar to the method we used in Listing 6-2, we specify the two tables to join around the JOIN keyword. Then we specify which columns we're joining on, in this case the id columns of both tables. Three school IDs match in both tables, so JOIN returns only the three rows of those IDs that match. Schools that exist only in one of the two tables don't appear in the result. Notice also that the columns from the left table display on the left of the result table:

```
id    left_school             id    right_school
--    ---------------------   --    ---------------------
 1    Oak Street School        1    Oak Street School
 2    Roosevelt High School    2    Roosevelt High School
 6    Jefferson High School    6    Jefferson High School
```

When should you use JOIN? Typically, when you're working with well-structured, well-maintained data sets and only need to find rows that exist in all the tables you're joining. Because JOIN doesn't provide rows that exist in only one of the tables, if you want to see all the data in one or more of the tables, use one of the other join types.

LEFT JOIN and RIGHT JOIN

In contrast, the LEFT JOIN and RIGHT JOIN keywords each return all rows from one table and display blank rows from the other table if no matching values are found in the joined columns. Let's look at the LEFT JOIN in action first. Execute the code in Listing 6-5:

```
SELECT *
FROM schools_left LEFT JOIN schools_right
ON schools_left.id = schools_right.id;
```

Listing 6-5: Using LEFT JOIN

The result of the query shows all four rows from schools_left as well as the three rows in schools_right where the id fields matched. Because schools_right doesn't contain a value of 5 in its right_id column, there's no match, so LEFT JOIN shows an empty row on the right rather than omitting the entire row from the left table as with JOIN. The rows from schools_right that don't match any values in schools_left are omitted from the results:

```
id    left_school                 id    right_school
--    ------------------------    --    ---------------------
 1    Oak Street School           1     Oak Street School
 2    Roosevelt High School       2     Roosevelt High School
 5    Washington Middle School
 6    Jefferson High School       6     Jefferson High School
```

We see similar but opposite behavior by running the `RIGHT JOIN` via the code in Listing 6-6:

```
SELECT *
FROM schools_left RIGHT JOIN schools_right
ON schools_left.id = schools_right.id;
```

Listing 6-6: Using `RIGHT JOIN`

This time, the query returns all rows from `schools_right` plus rows from `schools_left` where the `id` columns have matching values, but the query doesn't return the rows of `schools_left` that don't have a match with `schools_right`:

```
id    left_school              id    right_school
--    ---------------------    --    ---------------------
 1    Oak Street School         1    Oak Street School
 2    Roosevelt High School     2    Roosevelt High School
                                3    Morrison Elementary
                                4    Chase Magnet Academy
 6    Jefferson High School     6    Jefferson High School
```

You'd use either of these join types in a few circumstances:

- You want your query results to contain all the rows from one of the tables.
- You want to look for missing values in one of the tables; for example, when you're comparing data about an entity representing two different time periods.
- When you know some rows in a joined table won't have matching values.

FULL OUTER JOIN

When you want to see all rows from both tables in a join, regardless of whether any match, use the `FULL OUTER JOIN` option. To see it in action, run Listing 6-7:

```
SELECT *
FROM schools_left FULL OUTER JOIN schools_right
ON schools_left.id = schools_right.id;
```

Listing 6-7: Using `FULL OUTER JOIN`

The result gives every row from the left table, including matching rows and blanks for missing rows from the right table, followed by any leftover missing rows from the right table:

```
id    left_school                 id    right_school
--    ------------------------    --    --------------------
 1    Oak Street School            1    Oak Street School
 2    Roosevelt High School        2    Roosevelt High School
 5    Washington Middle School
 6    Jefferson High School        6    Jefferson High School
                                   4    Chase Magnet Academy
                                   3    Morrison Elementary
```

A `FULL OUTER JOIN` is admittedly less useful and used less often than inner and left or right joins. Still, you can use it for a couple of tasks: to merge two data sources that partially overlap or to visualize the degree to which the tables share matching values.

CROSS JOIN

In a `CROSS JOIN`, the result (also known as a *Cartesian Product*) lines up each row in the left table with each row in the right table to present all possible combinations of rows. Listing 6-8 shows the `CROSS JOIN` syntax; because the join doesn't need to find matches between key fields, there's no need to provide the clause using the `ON` keyword.

```
SELECT *
FROM schools_left CROSS JOIN schools_right;
```

Listing 6-8: Using `CROSS JOIN`

The result has 20 rows—the product of four rows in the left table times five rows in the right:

```
id    left_school                 id    right_school
--    ------------------------    --    --------------------
 1    Oak Street School            1    Oak Street School
 1    Oak Street School            2    Roosevelt High School
 1    Oak Street School            3    Morrison Elementary
 1    Oak Street School            4    Chase Magnet Academy
 1    Oak Street School            6    Jefferson High School
 2    Roosevelt High School        1    Oak Street School
 2    Roosevelt High School        2    Roosevelt High School
 2    Roosevelt High School        3    Morrison Elementary
 2    Roosevelt High School        4    Chase Magnet Academy
 2    Roosevelt High School        6    Jefferson High School
 5    Washington Middle School     1    Oak Street School
 5    Washington Middle School     2    Roosevelt High School
 5    Washington Middle School     3    Morrison Elementary
 5    Washington Middle School     4    Chase Magnet Academy
 5    Washington Middle School     6    Jefferson High School
```

```
6    Jefferson High School       1    Oak Street School
6    Jefferson High School       2    Roosevelt High School
6    Jefferson High School       3    Morrison Elementary
6    Jefferson High School       4    Chase Magnet Academy
6    Jefferson High School       6    Jefferson High School
```

Unless you want to take an extra-long coffee break, I'd suggest avoiding a `CROSS JOIN` query on large tables. Two tables with 250,000 records each would produce a result set of 62.5 *billion* rows and tax even the hardiest server. A more practical use would be generating data to create a checklist, such as all colors you'd want to offer for each shirt style in a warehouse.

Using NULL to Find Rows with Missing Values

Being able to reveal missing data from one of the tables is valuable when you're digging through data. Any time you join tables, it's wise to vet the quality of the data and understand it better by discovering whether all key values in one table appear in another. There are many reasons why a discrepancy might exist, such as a clerical error, the result of not getting complete output from the database, or some change in the data over time. All this information is important context for making correct inferences about the data.

When you have only a handful of rows, eyeballing the data is an easy way to look for rows with missing data. For large tables, you need a better strategy: filtering to show all rows without a match. To do this, we employ the keyword `NULL`.

In SQL, `NULL` is a special value that represents a condition in which there's no data present or where the data is unknown because it wasn't included. For example, if a person filling out an address form skips the "Middle Initial" field, rather than storing an empty string in the database, we'd use `NULL` to represent the unknown value. It's important to keep in mind that `NULL` is different from `0` or an empty string that you'd place in a character field using two quotes `""`. Both those values could have some unintended meaning that's open to misinterpretation, so you use `NULL` to show that the value is unknown for that row. And unlike `0` or an empty string, you can use `NULL` across data types.

When a SQL join returns empty rows in one of the tables, those columns don't come back empty but instead come back with the value `NULL`. In Listing 6-9, we'll find those rows by adding a `WHERE` clause to filter for `NULL` by using the phrase `IS NULL` on the `right_id` column. If we wanted to look for columns *with* data, we'd use `IS NOT NULL`.

```
SELECT *
FROM schools_left LEFT JOIN schools_right
ON schools_left.id = schools_right.id
WHERE schools_right.id IS NULL;
```

Listing 6-9: Filtering to show missing values with `IS NULL`

Now the result of the join shows only the one row from the left table that didn't have a match on the right side.

```
id    left_school                 id    right_school
--    ------------------------    --    ------------
 5    Washington Middle School
```

Using Relational Models to Join Tables

Part of the science of joining tables (or art, some may say) involves understanding how the database designer intends for the tables to relate, also known as the database's *relational model*. The three types of table relationships are one to one, one to many, and many to many.

One-to-One Model

In our `JOIN` example in Listing 6-4, there is only one match for an `id` in each of the two tables. In addition, there are no duplicate `id` values in either table: only one row in the left table exists with an `id` of `1`, and only one row in the right table has an `id` of `1`. In database parlance, this is called a *one-to-one* relationship. Consider another example: joining two tables with state-by-state census data. One table might contain household income data and the other data on educational attainment. Both tables would have 51 rows (one for each state plus Washington, D.C.), and if we wanted to join them on a key such as state name, state abbreviation, or a standard geography code, we'd have only one match for each key value in each table.

One-to-Many Model

In a *one-to-many* model, a key value in the first table will have multiple matching values in the second table's joined column. Consider a database that tracks automobiles. One table would hold data on automobile manufacturers, with one row each for Ford, Honda, Kia, and so on. A second table with model names, such as Focus, Civic, Sedona, and Accord, would have several rows matching each row in the manufacturers' table.

Many-to-Many Model

In a *many-to-many* model, multiple rows in the first table will have multiple matching rows in the second table. As an example, a table of baseball players could be joined to a table of field positions. Each player can be assigned to multiple positions, and each position can be played by multiple people.

Understanding these relationships is essential because it helps us discern whether the results of queries accurately reflect the structure of the database.

SELECT Specific Columns in a JOIN

So far, we've used the asterisk wildcard to select all columns from both tables. That's okay for quick data checks, but more often you'll want to specify a subset of columns. You can focus on just the data you want and avoid inadvertently changing the query results if someone adds a new column to a table.

As you learned in single-table queries, to select particular columns you use the `SELECT` keyword followed by the desired column names. When joining tables, the syntax changes slightly: you must include the column as well as its table name. The reason is that more than one table can contain columns with the same name, which is certainly true of our joined tables so far.

Consider the following query, which tries to fetch an `id` column without naming the table:

```
SELECT id
FROM schools_left LEFT JOIN schools_right
ON schools_left.id = schools_right.id;
```

Because `id` exists in both `schools_left` and `schools_right`, the server throws an error that appears in pgAdmin's results pane: `column reference "id" is ambiguous`. It's not clear which table `id` belongs to.

To fix the error, we need to add the table name in front of each column we're querying, as we do in the `ON` clause. Listing 6-10 shows the syntax:

```
SELECT schools_left.id,
       schools_left.left_school,
       schools_right.right_school
FROM schools_left LEFT JOIN schools_right
ON schools_left.id = schools_right.id;
```

Listing 6-10: Querying specific columns in a join

We simply prefix each column name with the table it comes from, and the rest of the query syntax is the same. The result returns the requested columns from each table:

```
id   left_school                right_school
--   ------------------------   --------------------
 1   Oak Street School          Oak Street School
 2   Roosevelt High School      Roosevelt High School
 5   Washington Middle School
 6   Jefferson High School      Jefferson High School
```

We can also add the `AS` keyword we used previously with census data to make it clear in the results that the `id` column is from `schools_left`. The syntax would look like this:

```
SELECT schools_left.id AS "left_id", ...
```

This would display the name of the `schools_left id` column as `left_id`. We could do this for all the other columns we select using the same syntax, but the next section describes another, better method we can use to rename multiple columns.

Simplifying JOIN Syntax with Table Aliases

Naming the table for a column is easy enough, but doing so for multiple columns clutters your code. One of the best ways to serve your colleagues is to write code that's readable, which should generally not involve making them wade through table names repeated for 25 columns! The way to write more concise code is to use a shorthand approach called *table aliases*.

To create a table alias, we place a character or two after the table name when we declare it in the `FROM` clause. (You can use more than a couple of characters for an alias, but if the goal is to simplify code, don't go overboard.) Those characters then serve as an alias we can use instead of the full table name anywhere we reference the table in the code. Listing 6-11 demonstrates how this works:

```
  SELECT lt.id,
         lt.left_school,
         rt.right_school
❶ FROM schools_left AS lt LEFT JOIN schools_right AS rt
  ON lt.id = rt.id;
```

Listing 6-11: Simplifying code with table aliases

In the `FROM` clause, we declare the alias `lt` to represent `schools_left` and the alias `rt` to represent `schools_right` ❶ using the `AS` keyword. Once that's in place, we can use the aliases instead of the full table names everywhere else in the code. Immediately, our SQL looks more compact, and that's ideal.

Joining Multiple Tables

Of course, SQL joins aren't limited to two tables. We can continue adding tables to the query as long as we have columns with matching values to join on. Let's say we obtain two more school-related tables and want to join them to `schools_left` in a three-table join. Here are the tables: `schools_enrollment` has the number of students per school:

```
id    enrollment
--    ----------
 1           360
 2          1001
 5           450
 6           927
```

The schools_grades table contains the grade levels housed in each building:

```
id   grades
--   ------
 1   K-3
 2   9-12
 5   6-8
 6   9-12
```

To write the query, we'll use Listing 6-12 to create the tables and load the data:

```
CREATE TABLE schools_enrollment (
    id integer,
    enrollment integer
);

CREATE TABLE schools_grades (
    id integer,
    grades varchar(10)
);

INSERT INTO schools_enrollment (id, enrollment)
VALUES
    (1, 360),
    (2, 1001),
    (5, 450),
    (6, 927);

INSERT INTO schools_grades (id, grades)
VALUES
    (1, 'K-3'),
    (2, '9-12'),
    (5, '6-8'),
    (6, '9-12');

SELECT lt.id, lt.left_school, en.enrollment, gr.grades
❶ FROM schools_left AS lt LEFT JOIN schools_enrollment AS en
    ON lt.id = en.id
❷ LEFT JOIN schools_grades AS gr
    ON lt.id = gr.id;
```

Listing 6-12: Joining multiple tables

After we run the CREATE TABLE and INSERT portions of the script, the results consist of schools_enrollment and schools_grades tables, each with records that relate to schools_left from earlier in the chapter. We then connect all three tables.

In the SELECT query, we join schools_left to schools_enrollment ❶ using the tables' id fields. We also declare table aliases to keep the code compact. Next, the query joins schools_left to school_grades again on the id fields ❷.

Our result now includes columns from all three tables:

```
id    left_school                enrollment    grades
--    ------------------------   ----------    ------
 1    Oak Street School                 360    K-3
 2    Roosevelt High School            1001    9-12
 5    Washington Middle School          450    6-8
 6    Jefferson High School             927    9-12
```

If you need to, you can add even more tables to the query using additional joins. You can also join on different columns, depending on the tables' relationships. Although there is no hard limit in SQL to the number of tables you can join in a single query, some database systems might impose one. Check the documentation.

Performing Math on Joined Table Columns

The math functions we explored in Chapter 5 are just as usable when working with joined tables. We just need to include the table name when referencing a column in an operation, as we did when selecting table columns. If you work with any data that has a new release at regular intervals, you'll find this concept useful for joining a newly released table to an older one and exploring how values have changed.

That's certainly what I and many journalists do each time a new set of census data is released. We'll load the new data and try to find patterns in the growth or decline of the population, income, education, and other indicators. Let's look at how to do this by revisiting the us_counties_2010 table we created in Chapter 4 and loading similar county data from the previous Decennial Census, in 2000, to a new table. Run the code in Listing 6-13, making sure you've saved the CSV file somewhere first:

```
❶ CREATE TABLE us_counties_2000 (
    geo_name varchar(90),
    state_us_abbreviation varchar(2),
    state_fips varchar(2),
    county_fips varchar(3),
    p0010001 integer,
    p0010002 integer,
    p0010003 integer,
    p0010004 integer,
    p0010005 integer,
    p0010006 integer,
    p0010007 integer,
    p0010008 integer,
```

```
    p0010009 integer,
    p0010010 integer,
    p0020002 integer,
    p0020003 integer
);

❷ COPY us_counties_2000
FROM 'C:\YourDirectory\us_counties_2000.csv'
WITH (FORMAT CSV, HEADER);

❸ SELECT c2010.geo_name,
       c2010.state_us_abbreviation AS state,
       c2010.p0010001 AS pop_2010,
       c2000.p0010001 AS pop_2000,
       c2010.p0010001 - c2000.p0010001 AS raw_change,
     ❹ round( (CAST(c2010.p0010001 AS numeric(8,1)) - c2000.p0010001)
           / c2000.p0010001 * 100, 1 ) AS pct_change
FROM us_counties_2010 c2010 INNER JOIN us_counties_2000 c2000
❺ ON c2010.state_fips = c2000.state_fips
   AND c2010.county_fips = c2000.county_fips
❻   AND c2010.p0010001 <> c2000.p0010001
❼ ORDER BY pct_change DESC;
```

Listing 6-13: Performing math on joined census tables

In this code, we're building on earlier foundations. We have the familiar `CREATE TABLE` statement ❶, which for this exercise includes state and county codes, a `geo_name` column with the full name of the state and county, and nine columns with population counts including total population and counts by race. The `COPY` statement ❷ imports a CSV file with the census data; you can find *us_counties_2000.csv* along with all of the book's resources at *https://www.nostarch.com/practicalSQL/*. After you've downloaded the file, you'll need to change the file path to the location where you saved it.

When you've finished the import, you should have a table named `us_counties_2000` with 3,141 rows. As with the 2010 data, this table has a column named `p0010001` that contains the total population for each county in the United States. Because both tables have the same column, it makes sense to calculate the percent change in population for each county between 2000 and 2010. Which counties have led the nation in growth? Which ones have a decline in population?

We'll use the percent change calculation we used in Chapter 5 to get the answer. The `SELECT` statement ❸ includes the county's name and state abbreviation from the 2010 table, which is aliased with `c2010`. Next are the `p0010001` total population columns from the 2010 and 2000 tables, both renamed with unique names using `AS` to distinguish them in the results. To get the raw change in population, we subtract the 2000 population from the 2010 count, and to find the percent change, we employ a formula ❹ and round the results to one decimal point.

We `JOIN` by matching values in two columns in both tables: `state_fips` and `county_fips` ❺. The reason to join on two columns instead of one is that in both tables, we need the combination of a state code and a county code to find a unique county. I've added a third condition ❻ to illustrate using an inequality. This limits the `JOIN` to counties where the `p0010001` population column has a different value. We combine all three conditions using the `AND` keyword. Using that syntax, a join happens when all three conditions are satisfied. Finally, the results are sorted in descending order by percent change ❼ so we can see the fastest growers at the top.

That's a lot of work, but it's worth it. Here's what the first five rows of the results indicate:

```
name             state   pop_2010   pop_2000   raw_change   pct_change
--------------   -----   --------   --------   ----------   ----------
Kendall County   IL        114736      54544        60192        110.4
Pinal County     AZ        375770     179727       196043        109.1
Flagler County   FL         95696      49832        45864         92.0
Lincoln County   SD         44828      24131        20697         85.8
Loudoun County   VA        312311     169599       142712         84.1
```

Two of America's counties, Kendall in Illinois and Pinal in Arizona, more than doubled their population in 10 years, with counties in Florida, South Dakota, and Virginia not far behind. That's a valuable story we've extracted from this analysis and a starting point for understanding national population trends. Many of the counties with the largest growth from 2000 to 2010 were suburban bedroom communities that benefited from the decade's housing boom. A more recent trend sees Americans leaving rural areas to move to cities. That will make for an interesting analysis following the 2020 Decennial Census.

Wrapping Up

Given that table relationships are foundational to database architecture, learning to join tables in queries allows you to handle many of the more complex data sets you'll encounter. Experimenting with the different types of joins on tables can tell you a great deal about how data have been gathered and reveal when there's a quality issue. Make trying various joins a routine part of your exploration of a new data set.

Moving forward, we'll continue building on these bigger concepts as we drill deeper into finding information in data sets and working with the finer nuances of handling data types and making sure we have quality data. But first, we'll look at one more foundational element: employing best practices to build reliable, speedy databases with SQL.

Try It Yourself

Continue your exploration of joins with these exercises:

1. The table `us_counties_2010` contains 3,143 rows, and `us_counties_2000` has 3,141. That reflects the ongoing adjustments to county-level geographies that typically result from government decision making. Using appropriate joins and the `NULL` value, identify which counties don't exist in both tables. For fun, search online to find out why they're missing.
2. Using either the `median()` or `percentile_cont()` functions in Chapter 5, determine the median percent change in county population.
3. Which county had the greatest percentage loss of population between 2000 and 2010? Do you have any idea why? Hint: a major weather event happened in 2005.

7

TABLE DESIGN THAT WORKS FOR YOU

Obsession with detail can be a good thing. When you're running out the door, it's reassuring to know your keys will be hanging on the hook where you *always* leave them. The same holds true for database design. When you need to excavate a nugget of information from dozens of tables and millions of rows, you'll appreciate a dose of that same detail obsession. When you organize data into a fine-tuned, smartly named set of tables, the analysis experience becomes more manageable.

In this chapter, I'll build on Chapter 6 by introducing *best practices* for organizing and tuning SQL databases, whether they're yours or ones you inherit for analysis. You already know how to create basic tables and add columns with the appropriate data type and a primary key. Now, we'll dig deeper into table design by exploring naming rules and conventions, ways to maintain the integrity of your data, and how to add indexes to tables to speed up queries.

Naming Tables, Columns, and Other Identifiers

Developers tend to follow different SQL style patterns when naming tables, columns, and other objects (called *identifiers*). Some prefer to use *camelCase*, as in `berrySmoothie`, where words are strung together and the first letter of each word is capitalized except for the first word. *PascalCase*, as in `BerrySmoothie`, follows a similar pattern but capitalizes the first letter of the first word too. With *snake_case*, as in `berry_smoothie`, all the words are lowercase and separated by underscores. So far, I've been using snake_case, such as in the table `us_counties_2010`.

You'll find passionate supporters of each naming convention, and some preferences are tied to individual database applications. For example, Microsoft recommends PascalCase for its SQL Server users. Whichever convention you prefer, it's most important to choose a style and apply it consistently. Be sure to check whether your organization has a style guide or offer to collaborate on one, and then follow it religiously.

Mixing styles or following none generally leads to a mess. It will be difficult to know which table is the most current, which is the backup, or the difference between two similarly named tables. For example, imagine connecting to a database and finding the following collection of tables:

```
Customers
customers
custBackup
customer_analysis
customer_test2
customer_testMarch2012
customeranalysis
```

In addition, working without a consistent naming scheme makes it problematic for others to dive into your data and makes it challenging for you to pick up where you left off.

Let's explore considerations related to naming identifiers and suggestions for best practices.

Using Quotes Around Identifiers to Enable Mixed Case

Standard ANSI SQL and many database-specific variants of SQL treat identifiers as case-insensitive unless you provide a delimiter around them—typically double quotes. Consider these two hypothetical `CREATE TABLE` statements for PostgreSQL:

```
CREATE TABLE customers (
    customer_id serial,
    --snip--
);

CREATE TABLE Customers (
    customer_id serial,
```

```
    --snip--
);
```

When you execute these statements in order, the first `CREATE TABLE` command creates a table called `customers`. But rather than creating a second table called `Customers`, the second statement will throw an error: `relation "customers" already exists`. Because you didn't quote the identifier, PostgreSQL treats `customers` and `Customers` as the same identifier, disregarding the case. If you want to preserve the uppercase letter and create a separate table named `Customers`, you must surround the identifier with quotes, like this:

```
CREATE TABLE "Customers" (
    customer_id serial,
    --snip--
);
```

Now, PostgreSQL retains the uppercase `C` and creates `Customers` as well as `customers`. Later, to query `Customers` rather than `customers`, you'll have to quote its name in the `SELECT` statement:

```
SELECT * FROM "Customers";
```

Of course, you wouldn't want two tables with such similar names because of the high risk of a mix-up. This example simply illustrates the behavior of SQL in PostgreSQL.

Pitfalls with Quoting Identifiers

Using quotation marks also permits characters not otherwise allowed in an identifier, including spaces. But be aware of the negatives of using this method: for example, you might want to throw quotes around `"trees planted"` and use that as a column name in a reforestation database, but then all users will have to provide quotes on every subsequent reference to that column. Omit the quotes and the database will respond with an error, identifying `trees` and `planted` as separate columns missing a comma between them. A more readable and reliable option is to use snake case, as in `trees_planted`.

Another downside to quoting is that it lets you use SQL *reserved keywords*, such as `TABLE`, `WHERE`, or `SELECT`, as an identifier. Reserved keywords are words SQL designates as having special meaning in the language. Most database developers frown on using reserved keywords as identifiers. At a minimum it's confusing, and at worst neglecting or forgetting to quote that keyword later will result in an error because the database will interpret the word as a command instead of an identifier.

NOTE: *For PostgreSQL, you can find a list of keywords documented at* https://www.postgresql.org/docs/current/static/sql-keywords-appendix.html. *In addition, many code editors and database tools, including pgAdmin, will automatically highlight keywords in a particular color.*

Guidelines for Naming Identifiers

Given the extra burden of quoting and its potential problems, it's best to keep your identifier names simple, unquoted, and consistent. Here are my recommendations:

- **Use snake_case**. Snake case is readable and reliable, as shown in the earlier `trees planted` example. It's used throughout the official PostgreSQL documentation and helps make multiword names easy to understand: `video_on_demand` makes more sense at a glance than `videoondemand`.
- **Make names easy to understand and avoid cryptic abbreviations**. If you're building a database related to travel, `arrival_time` is a better reminder of the content as a column name than `arv_tm`.
- **For table names, use plurals**. Tables hold rows, and each row represents one instance of an entity. So, use plural names for tables, such as `teachers`, `vehicles`, or `departments`.
- **Mind the length**. The maximum number of characters allowed for an identifier name varies by database application: the SQL standard is 128 characters, but PostgreSQL limits you to 63, and the Oracle system maximum is 30. If you're writing code that may get reused in another database system, lean toward shorter identifier names.
- **When making copies of tables, use names that will help you manage them later**. One method is to append a `YYYY_MM_DD` date to the table name when you create it, such as `tire_sizes_2017_10_20`. An additional benefit is that the table names will sort in date order.

Controlling Column Values with Constraints

A column's data type already broadly defines the kind of data it will accept: integers versus characters, for example. But SQL provides several additional *constraints* that let us further specify acceptable values for a column based on rules and logical tests. With constraints, we can avoid the "garbage in, garbage out" phenomenon, which is what happens when poor quality data result in inaccurate or incomplete analysis. Constraints help maintain the quality of the data and ensure the integrity of the relationships among tables.

In Chapter 6, you learned about *primary* and *foreign keys*, which are two of the most commonly used constraints. Let's review them as well as the following additional constraint types:

`CHECK` Evaluates whether the data falls within values we specify

`UNIQUE` Ensures that values in a column or group of columns are unique in each row in the table

`NOT NULL` Prevents `NULL` values in a column

We can add constraints in two ways: as a *column constraint* or as a *table constraint*. A column constraint only applies to that column. It's declared with the column name and data type in the `CREATE TABLE` statement, and it gets checked whenever a change is made to the column. With a table constraint, we can supply criteria that apply to one or more columns. We declare it in the `CREATE TABLE` statement immediately after defining all the table columns, and it gets checked whenever a change is made to a row in the table.

Let's explore these constraints, their syntax, and their usefulness in table design.

Primary Keys: Natural vs. Surrogate

In Chapter 6, you learned about giving a table a *primary key*: a column or collection of columns whose values uniquely identify each row in a table. A primary key is a constraint, and it imposes two rules on the column or columns that make up the key:

1. Each column in the key must have a unique value for each row.
2. No column in the key can have missing values.

Primary keys also provide a means of relating tables to each other and maintaining *referential integrity*, which is ensuring that rows in related tables have matching values when we expect them to. The simple primary key example in "Relating Tables with Key Columns" on page 74 had a single ID field that used an integer inserted by us, the user. However, as with most areas of SQL, you can implement primary keys in several ways. Often, the data will suggest the best path. But first we must assess whether to use a *natural key* or a *surrogate key* as the primary key.

Using Existing Columns for Natural Keys

You implement a natural key by using one or more of the table's existing columns rather than creating a column and filling it with artificial values to act as keys. If a column's values obey the primary key constraint—unique for every row and never empty—it can be used as a natural key. A value in the column can change as long as the new value doesn't cause a violation of the constraint.

An example of a natural key is a driver's license identification number issued by a local Department of Motor Vehicles. Within a governmental jurisdiction, such as a state in the United States, we'd reasonably expect that all drivers would receive a unique ID on their licenses. But if we were compiling a national driver license database, we may not be able to make that assumption; several states could independently issue the same ID code. In that case, the `driver_id` column may not have unique values and cannot be used as the natural key unless it's combined with one or more additional columns. Regardless, as you build tables, you'll encounter many values suitable for natural keys: a part number, a serial number, or a book's ISBN number are all good examples.

Introducing Columns for Surrogate Keys

Instead of relying on existing data, a surrogate key typically consists of a single column that you fill with artificial values. This might be a sequential number auto-generated by the database, such as the `serial` types you learned in Chapter 3. Some developers like to use a *universally unique identifier (UUID)*, which is a 32-hexadecimal-digit code that identifies computer hardware or software. Here's an example:

```
2911d8a8-6dea-4a46-af23-d64175a08237
```

Pros and Cons of Key Types

As with most SQL debates, there are arguments for using either type of primary key. Reasons cited for using natural keys often include the following:

- The data already exists in the table, and you don't need to add a column to create a key.
- Because the natural key data has meaning, it can reduce the need to join tables when searching.

Alternately, advocates of surrogate keys highlight these pros:

- Because a surrogate key doesn't have any meaning in itself and its values are independent of the data in the table, if your data changes later, you're not limited by the key structure.
- Natural keys tend to consume more storage than the integers typically used for surrogate keys.

A well-designed table should have one or more columns that can serve as a natural key. An example is a product table with a unique product code. But in a table of employees, it might be difficult to find any single column, or even multiple columns, that would be unique on a row-by-row basis to serve as a primary key. In that case, you can create a surrogate key, but you probably should reconsider the table structure.

Primary Key Syntax

In "`JOIN` Types" on page 78, you created primary keys on the `schools_left` and `schools_right` tables to try out `JOIN` types. In fact, these were surrogate keys: in both tables, you created columns called `id` to use as the key and used the keywords `CONSTRAINT key_name PRIMARY KEY` to declare them as primary keys. Let's work through several more primary key examples.

In Listing 7-1, we declare a primary key using the column constraint and table constraint methods on a table similar to the driver's license example mentioned earlier. Because we expect the driver's license IDs to always be unique, we'll use that column as a natural key.

```
CREATE TABLE natural_key_example (
❶   license_id varchar(10) CONSTRAINT license_key PRIMARY KEY,
    first_name varchar(50),
    last_name varchar(50)
);

❷ DROP TABLE natural_key_example;

CREATE TABLE natural_key_example (
    license_id varchar(10),
    first_name varchar(50),
    last_name varchar(50),
❸   CONSTRAINT license_key PRIMARY KEY (license_id)
);
```

Listing 7-1: Declaring a single-column natural key as a primary key

We first use the column constraint syntax to declare `license_id` as the primary key by adding the `CONSTRAINT` keyword ❶ followed by a name for the key and then the keywords `PRIMARY KEY`. An advantage of using this syntax is that it's easy to understand at a glance which column is designated as the primary key. Note that in the column constraint syntax you can omit the `CONSTRAINT` keyword and name for the key, and simply use `PRIMARY KEY`.

Next, we delete the table from the database by using the `DROP TABLE` command ❷ to prepare for the table constraint example.

To add the same primary key using the table constraint syntax, we declare the `CONSTRAINT` after listing the final column ❸ with the column we want to use as the key in parentheses. In this example, we end up with the same column for the primary key as we did with the column constraint syntax. However, you must use the table constraint syntax when you want to create a primary key using more than one column. In that case, you would list the columns in parentheses, separated by commas. We'll explore that in a moment.

First, let's look at how having a primary key protects you from ruining the integrity of your data. Listing 7-2 contains two `INSERT` statements:

```
INSERT INTO natural_key_example (license_id, first_name, last_name)
VALUES ('T229901', 'Lynn', 'Malero');

INSERT INTO natural_key_example (license_id, first_name, last_name)
VALUES ('T229901', 'Sam', 'Tracy');
```

Listing 7-2: Example of a primary key violation

When you execute the first `INSERT` statement on its own, the server loads a row into the `natural_key_example` table without any issue. When you attempt to execute the second, the server replies with an error:

```
ERROR:  duplicate key value violates unique constraint "license_key"
DETAIL:  Key (license_id)=(T229901) already exists.
```

Before adding the row, the server checked whether a `license_id` of `T229901` was already present in the table. Because it was and because a primary key by definition must be unique for each row, the server rejected the operation. The rules of the fictional DMV state that no two drivers can have the same license id, so checking for and rejecting duplicate data is one way for the database to enforce that rule.

Creating a Composite Primary Key

If we want to create a natural key but a single column in the table isn't sufficient for meeting the primary key requirements for uniqueness, we may be able to create a suitable key from a combination of columns, which is called a *composite primary key*.

As a hypothetical example, let's use a table that tracks student school attendance. The combination of a student ID column and a date column would give us unique data for each row, tracking whether or not the student was in school each day during a school year. To create a composite primary key from two or more columns, you must declare it using the table constraint syntax mentioned earlier. Listing 7-3 creates an example table for the student attendance scenario. The school database would record each `student_id` only once per `school_day`, creating a unique value for the row. A `present` column of data type `boolean` indicates whether the student was there on that day.

```
CREATE TABLE natural_key_composite_example (
    student_id varchar(10),
    school_day date,
    present boolean,
    CONSTRAINT student_key PRIMARY KEY (student_id, school_day)
);
```

Listing 7-3: Declaring a composite primary key as a natural key

The syntax in Listing 7-3 follows the same table constraint format for adding a primary key for one column, but we pass two (or more) columns as arguments rather than one. Again, we can simulate a key violation by attempting to insert a row where the combination of values in the two key columns—`student_id` and `school_day`—is not unique to the table. Run the code in Listing 7-4:

```
INSERT INTO natural_key_composite_example (student_id, school_day, present)
VALUES(775, '1/22/2017', 'Y');

INSERT INTO natural_key_composite_example (student_id, school_day, present)
VALUES(775, '1/23/2017', 'Y');

INSERT INTO natural_key_composite_example (student_id, school_day, present)
VALUES(775, '1/23/2017', 'N');
```

Listing 7-4: Example of a composite primary key violation

The first two INSERT statements execute fine because there's no duplication of values in the combination of key columns. But the third statement causes an error because the student_id and school_day values it contains match a combination that already exists in the table:

```
ERROR:  duplicate key value violates unique constraint "student_key"
DETAIL:  Key (student_id, school_day)=(775, 2017-01-23) already exists.
```

You can create composite keys with more than two columns. The specific database you're using imposes the limit to the number of columns you can use.

Creating an Auto-Incrementing Surrogate Key

If a table you're creating has no columns suitable for a natural primary key, you may have a data integrity problem; in that case, it's best to reconsider how you're structuring the database. If you're inheriting data for analysis or feel strongly about using surrogate keys, you can create a column and fill it with unique values. Earlier, I mentioned that some developers use UUIDs for this; others rely on software to generate a unique code. For our purposes, an easy way to create a surrogate primary key is with an auto-incrementing integer using one of the serial data types discussed in Chapter 3, in "Auto-Incrementing Integers" on page 27.

Recall the three serial types: smallserial, serial, and bigserial. They correspond to the integer types smallint, integer, and bigint in terms of the range of values they handle and the amount of disk storage they consume. For a primary key, it may be tempting to try to save disk space by using serial, which handles numbers as large as 2,147,483,647. But many a database developer has received a late-night call from a user frantic to know why their application is broken, only to discover that the database is trying to generate a number one greater than the data type maximum. For this reason, with PostgreSQL, it's generally wise to use bigserial, which accepts numbers as high as 9.2 *quintillion*. You can set it and forget it, as shown in the first column defined in Listing 7-5:

```
CREATE TABLE surrogate_key_example (
❶    order_number bigserial,
     product_name varchar(50),
     order_date date,
❷    CONSTRAINT order_key PRIMARY KEY (order_number)
);

❸ INSERT INTO surrogate_key_example (product_name, order_date)
VALUES ('Beachball Polish', '2015-03-17'),
       ('Wrinkle De-Atomizer', '2017-05-22'),
       ('Flux Capacitor', '1985-10-26');

SELECT * FROM surrogate_key_example;
```

Listing 7-5: Declaring a bigserial column as a surrogate key

Listing 7-5 shows how to declare the `bigserial` ❶ data type for an `order_number` column and set the column as the primary key ❷. When you insert data into the table ❸, you can omit the `order_number` column. With `order_number` set to `bigserial`, the database will create a new value for that column on each insert. The new value will be one greater than the largest already created for the column.

Run `SELECT * FROM surrogate_key_example;` to see how the column fills in automatically:

```
order_number    product_name          order_date
------------    -------------------   ----------
           1    Beachball Polish      2015-03-17
           2    Wrinkle De-Atomizer   2017-05-22
           3    Flux Capacitor        1985-10-26
```

The database will add one to `order_number` each time a new row is inserted. But it won't fill any gaps in the sequence created after rows are deleted.

Foreign Keys

With the *foreign key* constraint, SQL very helpfully provides a way to ensure data in related tables doesn't end up unrelated, or orphaned. A foreign key is one or more columns in a table that match the primary key of another table. But a foreign key also imposes a constraint: values entered must already exist in the primary key or other unique key of the table it references. If not, the value is rejected. This constraint ensures that we don't end up with rows in one table that have no relation to rows in the other tables we can join them to.

To illustrate, Listing 7-6 shows two tables from a hypothetical database tracking motor vehicle activity:

```
CREATE TABLE licenses (
    license_id varchar(10),
    first_name varchar(50),
    last_name varchar(50),
❶   CONSTRAINT licenses_key PRIMARY KEY (license_id)
);
CREATE TABLE registrations (
    registration_id varchar(10),
    registration_date date,
❷   license_id varchar(10) REFERENCES licenses (license_id)
);

❸ INSERT INTO licenses (license_id, first_name, last_name)
VALUES ('T229901', 'Lynn', 'Malero');

❹ INSERT INTO registrations (registration_id, registration_date, license_id)
VALUES ('A203391', '3/17/2017', 'T229901');
```

```
❺ INSERT INTO registrations (registration_id, registration_date, license_id)
  VALUES ('A203391', '3/17/2017', 'T000001');
```

Listing 7-6: A foreign key example

The first table, licenses, is similar to the natural_key_example table we made earlier and uses a driver's unique license_id ❶ as a natural primary key. The second table, registrations, is for tracking vehicle registrations. A single license ID might be connected to multiple vehicle registrations, because each licensed driver can register multiple vehicles over a number of years. Also, a single vehicle could be registered to multiple license holders, establishing, as you learned in Chapter 6, a *many-to-many* relationship.

Here's how that relationship is expressed via SQL: in the registrations table, we designate the column license_id as a foreign key by adding the REFERENCES keyword followed by the table name and column for it to reference ❷.

Now, when we insert a row into registrations, the database will test whether the value inserted into license_id already exists in the license_id primary key column of the licenses table. If it doesn't, the database returns an error, which is important. If any rows in registrations didn't correspond to a row in licenses, we'd have no way to write a query to find the person who registered the vehicle.

To see this constraint in action, create the two tables and execute the INSERT statements one at a time. The first adds a row to licenses ❸ that includes the value T229901 for the license_id. The second adds a row to registrations ❹ where the foreign key contains the same value. So far, so good, because the value exists in both tables. But we encounter an error with the third insert, which tries to add a row to registrations ❺ with a value for license_id that's not in licenses:

```
ERROR:  insert or update on table "registrations" violates foreign key
constraint "registrations_license_id_fkey"
DETAIL:  Key (license_id)=(T000001) is not present in table "licenses".
```

The resulting error is good because it shows the database is keeping the data clean. But it also indicates a few practical implications: first, it affects the order we insert data. We cannot add data to a table that contains a foreign key before the other table referenced by the key has the related records, or we'll get an error. In this example, we'd have to create a driver's license record before inserting a related registration record (if you think about it, that's what your local department of motor vehicles probably does).

Second, the reverse applies when we delete data. To maintain referential integrity, the foreign key constraint prevents us from deleting a row from licenses before removing any related rows in registrations, because doing so would leave an orphaned record. We would have to delete the related row in registrations first, and then delete the row in licenses. However, ANSI SQL provides a way to handle this order of operations automatically using the ON DELETE CASCADE keywords, which I'll discuss next.

Automatically Deleting Related Records with CASCADE

To delete a row in `licenses` and have that action automatically delete any related rows in `registrations`, we can specify that behavior by adding `ON DELETE CASCADE` when defining the foreign key constraint.

When we create the `registrations` table, the keywords would go at the end of the definition of the `license_id` column, like this:

```
CREATE TABLE registrations (
    registration_id varchar(10),
    registration_date date,
    license_id varchar(10) REFERENCES licenses (license_id) ON DELETE CASCADE
);
```

Now, deleting a row in `licenses` should also delete all related rows in `registrations`. This allows us to delete a driver's license without first having to manually remove any registrations to it. It also maintains data integrity by ensuring deleting a license doesn't leave orphaned rows in `registrations`.

The CHECK Constraint

A `CHECK` constraint evaluates whether data added to a column meets the expected criteria, which we specify with a logical test. If the criteria isn't met, the database returns an error. `CHECK` constraints are extremely valuable because they can prevent columns from getting loaded with nonsensical data. For example, a new employee's birth date probably shouldn't be more than 120 years in the past, so you can set a cap on birth dates. Or, in most schools I know, `Z` isn't a valid letter grade for a course (although my barely passing algebra grade felt like it), so we might insert constraints that only accept the values A–F.

As with primary keys, we can implement a `CHECK` constraint as a column constraint or a table constraint. For a column constraint, declare it in the `CREATE TABLE` statement after the column name and data type: `CHECK (`*`logical expression`*`)`. As a table constraint, use the syntax `CONSTRAINT` *`constraint_name`* `CHECK (`*`logical expression`*`)` after all columns are defined.

Listing 7-7 shows a `CHECK` constraint applied to two columns in a table we might use to track the user role and salary of employees within an organization. It uses the table constraint syntax for the primary key and the `CHECK` constraint.

```
CREATE TABLE check_constraint_example (
    user_id bigserial,
    user_role varchar(50),
    salary integer,
    CONSTRAINT user_id_key PRIMARY KEY (user_id),
❶   CONSTRAINT check_role_in_list CHECK (user_role IN('Admin', 'Staff')),
❷   CONSTRAINT check_salary_not_zero CHECK (salary > 0)
);
```

Listing 7-7: `CHECK` *constraint examples*

We create the table and set the `user_id` column as an auto-incrementing surrogate primary key. The first `CHECK` ❶ tests whether values entered into the `user_role` column match one of two predefined strings, `Admin` or `Staff`, by using the SQL `IN` operator. The second `CHECK` tests whether values entered in the `salary` column are greater than 0, because no one should be earning a negative amount ❷. Both tests are another example of a *Boolean expression*, a statement that evaluates as either true or false. If a value tested by the constraint evaluates as true, the check passes.

NOTE *Developers may debate whether check logic belongs in the database, in the application in front of the database, such as a human resources system, or both. One advantage of checks in the database is that the database will maintain data integrity in the case of changes to the application, even if a new system gets built or users are given alternate ways to add data.*

When values are inserted or updated, the database checks them against the constraint. If the values in either column violate the constraint—or, for that matter, if the primary key constraint is violated—the database will reject the change.

If we use the table constraint syntax, we also can combine more than one test in a single `CHECK` statement. Say we have a table related to student achievement. We could add the following:

```
CONSTRAINT grad_check CHECK (credits >= 120 AND tuition = 'Paid')
```

Notice that we combine two logical tests by enclosing them in parentheses and connecting them with `AND`. Here, both Boolean expressions must evaluate as true for the entire check to pass. You can also test values across columns, as in the following example where we want to make sure an item's sale price is a discount on the original, assuming we have columns for both values:

```
CONSTRAINT sale_check CHECK (sale_price < retail_price)
```

Inside the parentheses, we provide criteria that indicates the sale price needs to be less than the retail price.

The UNIQUE Constraint

We can also ensure that a column has a unique value in each row by using the `UNIQUE` constraint. If ensuring unique values sounds similar to the purpose of a primary key, it is. But `UNIQUE` has one important difference. In a primary key, no values can be `NULL`, but a `UNIQUE` constraint permits multiple `NULL` values in a column.

To show the usefulness of `UNIQUE`, look at the code in Listing 7-8, which is a table for tracking contact info:

```
CREATE TABLE unique_constraint_example (
    contact_id bigserial CONSTRAINT contact_id_key PRIMARY KEY,
```

```
    first_name varchar(50),
    last_name varchar(50),
    email varchar(200),
❶   CONSTRAINT email_unique UNIQUE (email)
);

INSERT INTO unique_constraint_example (first_name, last_name, email)
VALUES ('Samantha', 'Lee', 'slee@example.org');

INSERT INTO unique_constraint_example (first_name, last_name, email)
VALUES ('Betty', 'Diaz', 'bdiaz@example.org');

INSERT INTO unique_constraint_example (first_name, last_name, email)
❷ VALUES ('Sasha', 'Lee', 'slee@example.org');
```

Listing 7-8: `UNIQUE` constraint example

In this table, `contact_id` serves as a surrogate primary key, uniquely identifying each row. But we also have an `email` column, the main point of contact with each person. We'd expect this column to contain only unique email addresses, but those addresses might change over time. So, we use `UNIQUE` ❶ to ensure that any time we add or update a contact's email we're not providing one that already exists. If we do try to insert an email that already exists ❷, the database will return an error:

```
ERROR:  duplicate key value violates unique constraint "email_unique"
DETAIL:  Key (email)=(slee@example.org) already exists.
```

Again, the error shows the database is working for us.

The NOT NULL Constraint

In Chapter 6, you learned about `NULL`, a special value in SQL that represents a condition where no data is present in a row in a column or the value is unknown. You've also learned that `NULL` values are not allowed in a primary key, because primary keys need to uniquely identify each row in a table. But there will be other columns besides primary keys where you don't want to allow empty values. For example, in a table listing each student in a school, it would be necessary for columns containing first and last names to be filled for each row. To require a value in a column, SQL provides the `NOT NULL` constraint, which simply prevents a column from accepting empty values.

Listing 7-9 demonstrates the `NOT NULL` syntax:

```
CREATE TABLE not_null_example (
    student_id bigserial,
    first_name varchar(50) NOT NULL,
    last_name varchar(50) NOT NULL,
    CONSTRAINT student_id_key PRIMARY KEY (student_id)
);
```

Listing 7-9: `NOT NULL` constraint example

Here, we declare NOT NULL for the first_name and last_name columns because it's likely we'd require those pieces of information in a table tracking student information. If we attempt an INSERT on the table and don't include values for those columns, the database will notify us of the violation.

Removing Constraints or Adding Them Later

So far, we've been placing constraints on tables at the time of creation. You can also remove a constraint or later add one to an existing table using ALTER TABLE, the SQL command that makes changes to tables and columns. We'll work with ALTER TABLE more in Chapter 9, but for now we'll review the syntax for adding and removing constraints.

To remove a primary key, foreign key, or a UNIQUE constraint, you would write an ALTER TABLE statement in this format:

```
ALTER TABLE table_name DROP CONSTRAINT constraint_name;
```

To drop a NOT NULL constraint, the statement operates on the column, so you must use the additional ALTER COLUMN keywords, like so:

```
ALTER TABLE table_name ALTER COLUMN column_name DROP NOT NULL;
```

Let's use these statements to modify the not_null_example table you just made, as shown in Listing 7-10:

```
ALTER TABLE not_null_example DROP CONSTRAINT student_id_key;
ALTER TABLE not_null_example ADD CONSTRAINT student_id_key PRIMARY KEY (student_id);
ALTER TABLE not_null_example ALTER COLUMN first_name DROP NOT NULL;
ALTER TABLE not_null_example ALTER COLUMN first_name SET NOT NULL;
```

Listing 7-10: Dropping and adding a primary key and a NOT NULL *constraint*

Execute the statements one at a time to make changes to the table. Each time, you can view the changes to the table definition in pgAdmin by clicking the table name once, and then clicking the **SQL** tab above the query window. With the first ALTER TABLE statement, we use DROP CONSTRAINT to remove the primary key named student_id_key. We then add the primary key back using ADD CONSTRAINT. We'd use that same syntax to add a constraint to any existing table.

NOTE *You can only add a constraint to an existing table if the data in the target column obeys the limits of the constraint. For example, you can't place a primary key constraint on a column that has duplicate or empty values.*

ALTER COLUMN and DROP NOT NULL remove the NOT NULL constraint from the first_name column in the third statement. Finally, SET NOT NULL adds the constraint.

Speeding Queries with Indexes

In the same way that a book's index helps you find information more quickly, you can speed up queries by adding an *index* to one or more columns. The database uses the index as a shortcut rather than scanning each row to find data. That's admittedly a simplistic picture of what, in SQL databases, is a nontrivial topic. I could write several chapters on SQL indexes and tuning databases for performance, but instead I'll offer general guidance on using indexes and a PostgreSQL-specific example that demonstrates their benefits.

B-Tree, PostgreSQL's Default Index

While following along in this book, you've already created several indexes, perhaps without knowing. Each time you add a primary key or `UNIQUE` constraint to a table, PostgreSQL (as well as most database systems) places an index on the column. Indexes are stored separately from the table data, but they're accessed automatically when you run a query and are updated every time a row is added or removed from the table.

In PostgreSQL, the default index type is the *B-Tree index*. It's created automatically on the columns designated for the primary key or a `UNIQUE` constraint, and it's also the type created by default when you execute a `CREATE INDEX` statement. B-Tree, short for *balanced tree*, is so named because the structure organizes the data in a way that when you search for a value, it looks from the top of the tree down through branches until it locates the data you want. (Of course, the process is a lot more complicated than that. A good start on understanding more about the B-Tree is the B-Tree Wikipedia entry.) A B-Tree index is useful for data that can be ordered and searched using equality and range operators, such as `<`, `<=`, `=`, `>=`, `>`, and `BETWEEN`.

PostgreSQL incorporates additional index types, including the *Generalized Inverted Index (GIN)* and the *Generalized Search Tree (GiST)*. Each has distinct uses, and I'll incorporate them in later chapters on full text search and queries using geometry types.

For now, let's see a B-Tree index speed a simple search query. For this exercise, we'll use a large dataset comprising more than 900,000 New York City street addresses, compiled by the OpenAddresses project at *https://openaddresses.io/*. The file with the data, *city_of_new_york.csv*, is available for you to download along with all the resources for this book from *https://www.nostarch.com/practicalSQL/*.

After you've downloaded the file, use the code in Listing 7-11 to create a `new_york_addresses` table and import the address data. You're a pro at this by now, although the import will take longer than the tiny datasets you've loaded so far. The final, loaded table is 126MB, and on one of my systems, it took nearly a minute for the `COPY` command to complete.

```
CREATE TABLE new_york_addresses (
    longitude numeric(9,6),
    latitude numeric(9,6),
```

```
    street_number varchar(10),
    street varchar(32),
    unit varchar(7),
    postcode varchar(5),
    id integer CONSTRAINT new_york_key PRIMARY KEY
);

COPY new_york_addresses
FROM 'C:\YourDirectory\city_of_new_york.csv'
WITH (FORMAT CSV, HEADER);
```

Listing 7-11: Importing New York City address data

When the data loads, run a quick `SELECT` query to visually check that you have 940,374 rows and eight columns. A common use for this data might be to search for matches in the `street` column, so we'll use that example for exploring index performance.

Benchmarking Query Performance with EXPLAIN

We'll measure how well an index can improve query speed by checking the performance before and after adding one. To do this, we'll use PostgreSQL's `EXPLAIN` command, which is specific to PostgreSQL and not part of standard SQL. The `EXPLAIN` command provides output that lists the *query plan* for a specific database query. This might include how the database plans to scan the table, whether or not it will use indexes, and so on. If we add the `ANALYZE` keyword, `EXPLAIN` will carry out the query and show the actual execution time, which is what we want for the current exercise.

Recording Some Control Execution Times

Run each of the three queries in Listing 7-12 one at a time. We're using typical `SELECT` queries with a `WHERE` clause but with the keywords `EXPLAIN ANALYZE` included at the beginning. Instead of showing the query results, these keywords tell the database to execute the query and display statistics about the query process and how long it took to execute.

```
EXPLAIN ANALYZE SELECT * FROM new_york_addresses
WHERE street = 'BROADWAY';

EXPLAIN ANALYZE SELECT * FROM new_york_addresses
WHERE street = '52 STREET';

EXPLAIN ANALYZE SELECT * FROM new_york_addresses
WHERE street = 'ZWICKY AVENUE';
```

Listing 7-12: Benchmark queries for index performance

On my system, the first query returns these stats:

```
❶ Seq Scan on new_york_addresses  (cost=0.00..20730.68 rows=3730 width=46)
(actual time=0.055..289.426 rows=3336 loops=1)
     Filter: ((street)::text = 'BROADWAY'::text)
```

```
   Rows Removed by Filter: 937038
 Planning time: 0.617 ms
❷ Execution time: 289.838 ms
```

Not all the output is relevant here, so I won't decode it all, but two lines are pertinent. The first indicates that to find any rows where `street = 'BROADWAY'`, the database will conduct a sequential scan ❶ of the table. That's a synonym for a full table scan: each row will be examined, and the database will remove any row that doesn't match `BROADWAY`. The execution time (on my computer about 290 milliseconds) ❷ is how long this will take. Your time will depend on factors including your computer hardware.

Run each query in Listing 7-12 and record the execution time for each.

Adding the Index

Now, let's see how adding an index changes the query's search method and how fast it works. Listing 7-13 shows the SQL for creating the index with PostgreSQL:

```
CREATE INDEX street_idx ON new_york_addresses (street);
```

Listing 7-13: Creating a B-Tree index on the new_york_addresses table

Notice that it's similar to the commands for creating constraints we've covered in the chapter already. (Other database systems have their own variants and options for creating indexes, and there is no ANSI standard.) We give the `CREATE INDEX` keywords followed by a name we choose for the index, in this case `street_idx`. Then `ON` is added, followed by the target table and column.

Execute the `CREATE INDEX` statement, and PostgreSQL will scan the values in the `street` column and build the index from them. We only need to create the index once. When the task finishes, rerun each of the three queries in Listing 7-12 and record the execution times reported by `EXPLAIN ANALYZE`. For example:

```
 Bitmap Heap Scan on new_york_addresses  (cost=65.80..5962.17 rows=2758
width=46) (actual time=1.792..9.816 rows=3336 loops=1)
   Recheck Cond: ((street)::text = 'BROADWAY'::text)
   Heap Blocks: exact=2157
❶    ->  Bitmap Index Scan on street_idx  (cost=0.00..65.11 rows=2758 width=0)
(actual time=1.253..1.253 rows=3336 loops=1)
         Index Cond: ((street)::text = 'BROADWAY'::text)
 Planning time: 0.163 ms
❷ Execution time: 5.887 ms
```

Do you notice a change? First, instead of a sequential scan, the `EXPLAIN ANALYZE` statistics for each query show that the database is now using an index scan on `street_idx` ❶ instead of visiting each row. Also, the query speed is now markedly faster ❷. Table 7-1 shows the execution times (rounded) from my computer before and after adding the index.

Table 7-1: Measuring Index Performance

Query Filter	Before Index	After Index
WHERE street = 'BROADWAY'	290 ms	6 ms
WHERE street = '52 STREET'	271 ms	6 ms
WHERE street = 'ZWICKY AVENUE'	306 ms	1 ms

The execution times are much, much better, effectively a quarter second faster or more per query. Is a quarter second that impressive? Well, whether you're seeking answers in data using repeated querying or creating a database system for thousands of users, the time savings adds up.

If you ever need to remove an index from a table—perhaps if you're testing the performance of several index types—use the `DROP INDEX` command followed by the name of the index to remove.

Considerations When Using Indexes

You've seen that indexes have significant performance benefits, so does that mean you should add an index to every column in a table? Not so fast! Indexes are valuable, but they're not always needed. In addition, they do enlarge the database and impose a maintenance cost on writing data. Here are a few tips for judging when to uses indexes:

- Consult the documentation for the database manager you're using to learn about the kinds of indexes available and which to use on particular data types. PostgreSQL, for example, has five more index types in addition to B-Tree. One, called GiST, is particularly suited to the geometry data types I'll discuss later in the book. Full text search, which you'll learn in Chapter 13, also benefits from indexing.
- Consider adding indexes to any columns you'll use in table joins. Primary keys are indexed by default in PostgreSQL, but foreign key columns in related tables are not and are a good target for indexes.
- Add indexes to columns that will frequently end up in a query `WHERE` clause. As you've seen, search performance is significantly improved via indexes.
- Use `EXPLAIN ANALYZE` to test performance under a variety of configurations if you're unsure. Optimization is a process!

Wrapping Up

With the tools you've added to your tool box in this chapter, you're ready to ensure that the databases you build or inherit are best suited for your collection and exploration of data. Your queries will run faster, you can exclude unwanted values, and your database objects will have consistent organization. That's a boon for you and for others who share your data.

This chapter concludes the first part of the book, which focused on giving you the essentials to dig into SQL databases. I'll continue building on these foundations as we explore more complex queries and strategies for data analysis. In the next chapter, we'll use SQL aggregate functions to assess the quality of a dataset and get usable information from it.

Try It Yourself

Are you ready to test yourself on the concepts covered in this chapter? Consider the following two tables from a database you're making to keep track of your vinyl LP collection. Start by reviewing these `CREATE TABLE` statements:

```
CREATE TABLE albums (
    album_id bigserial,
    album_catalog_code varchar(100),
    album_title text,
    album_artist text,
    album_release_date date,
    album_genre varchar(40),
    album_description text
);

CREATE TABLE songs (
    song_id bigserial,
    song_title text,
    song_artist text,
    album_id bigint
);
```

The `albums` table includes information specific to the overall collection of songs on the disc. The `songs` table catalogs each track on the album. Each song has a title and its own artist column, because each song might feature its own collection of artists.

Use the tables to answer these questions:

1. Modify these `CREATE TABLE` statements to include primary and foreign keys plus additional constraints on both tables. Explain why you made your choices.
2. Instead of using `album_id` as a surrogate key for your primary key, are there any columns in `albums` that could be useful as a natural key? What would you have to know to decide?
3. To speed up queries, which columns are good candidates for indexes?

8

EXTRACTING INFORMATION BY GROUPING AND SUMMARIZING

Every dataset tells a story, and it's the data analyst's job to find out what that story is. In Chapter 2, you learned about interviewing data using SELECT statements, which included sorting columns, finding distinct values, and filtering results. You've also learned the fundamentals of SQL math, data types, table design, and joining tables. With all these tools under your belt, you're ready to summarize data using grouping and SQL functions.

Summarizing data allows us to identify useful information we wouldn't be able to see otherwise. In this chapter, we'll use the well-known institution of your local library as our example.

Despite changes in the way people consume information, libraries remain a vital part of communities worldwide. But the internet and advancements in library technology have changed how we use libraries. For example, ebooks and online access to digital materials now have a permanent place in libraries along with books and periodicals.

In the United States, the Institute of Museum and Library Services (IMLS) measures library activity as part of its annual Public Libraries Survey. The survey collects data from more than 9,000 library administrative entities, defined by the survey as agencies that provide library services to a particular locality. Some agencies are county library systems, and others are part of school districts. Data on each agency includes the number of branches, staff, books, hours open per year, and so on. The IMLS has been collecting data each year since 1988 and includes all public library agencies in the 50 states plus the District of Columbia and several territories, such as American Samoa. (Read more on the program at *https://www.imls.gov/research-evaluation/data-collection/public-libraries-survey/*.)

For this exercise, we'll assume the role of an analyst who just received a fresh copy of the library dataset to produce a report describing trends from the data. We'll need to create two tables, one with data from the 2014 survey and the second from the 2009 survey. Then we'll summarize the more interesting data in each table and join the tables to see trends over the five years. During the analysis, you'll learn SQL techniques for summarizing data using *aggregate functions* and *grouping*.

Creating the Library Survey Tables

Let's create the 2014 and 2009 library survey tables and import the data. We'll use appropriate data types for each column and add constraints and an index to each table to preserve data integrity and speed queries.

Creating the 2014 Library Data Table

We'll start by creating the table for the 2014 library data. Using the `CREATE TABLE` statement, Listing 8-1 builds `pls_fy2014_pupld14a`, a table for the fiscal year 2014 Public Library Data File from the Public Libraries Survey. The Public Library Data File summarizes data at the agency level, counting activity at all agency outlets, which include central libraries, branch libraries, and bookmobiles. The annual survey generates two additional files we won't use: one summarizes data at the state level, and the other has data on individual outlets. For this exercise, those files are redundant, but you can read about the data they contain in the 2014 data dictionary, available from the IMLS at *https://www.imls.gov/sites/default/files/fy2014_pls_data_file_documentation.pdf*.

For convenience, I've created a naming scheme for the tables: `pls` refers to the survey title, `fy2014` is the fiscal year the data covers, and `pupld14a` is the name of the particular file from the survey. For simplicity, I've selected just 72 of the more relevant columns from the 159 in the original survey file to fill the `pls_fy2014_pupld14a` table, excluding data like the codes that explain the source of individual responses. When a library didn't provide data, the agency derived the data using other means, but we don't need that information for this exercise.

Note that Listing 8-1 is abbreviated for convenience. The full dataset and code for creating and loading this table is available for download with all the book's resources at *https://www.nostarch.com/practicalSQL/*.

```
CREATE TABLE pls_fy2014_pupld14a (
    stabr varchar(2) NOT NULL,
❶   fscskey varchar(6) CONSTRAINT fscskey2014_key PRIMARY KEY,
    libid varchar(20) NOT NULL,
    libname varchar(100) NOT NULL,
    obereg varchar(2) NOT NULL,
    rstatus integer NOT NULL,
    statstru varchar(2) NOT NULL,
    statname varchar(2) NOT NULL,
    stataddr varchar(2) NOT NULL,
    --snip--
    wifisess integer NOT NULL,
    yr_sub integer NOT NULL
);

❷ CREATE INDEX libname2014_idx ON pls_fy2014_pupld14a (libname);
CREATE INDEX stabr2014_idx ON pls_fy2014_pupld14a (stabr);
CREATE INDEX city2014_idx ON pls_fy2014_pupld14a (city);
CREATE INDEX visits2014_idx ON pls_fy2014_pupld14a (visits);

❸ COPY pls_fy2014_pupld14a
FROM 'C:\YourDirectory\pls_fy2014_pupld14a.csv'
WITH (FORMAT CSV, HEADER);
```

Listing 8-1: Creating and filling the 2014 Public Libraries Survey table

After finding the code and data file for Listing 8-1, connect to your `analysis` database in pgAdmin and run it. Remember to change *C:\YourDirectory* to the path where you saved the CSV file.

Here's what it does: first, the code makes the table via `CREATE TABLE`. We assign a primary key constraint to the column named `fscskey` ❶, a unique code the data dictionary says is assigned to each library. Because it's unique, present in each row, and unlikely to change, it can serve as a natural primary key.

The definition for each column includes the appropriate data type and `NOT NULL` constraints where the columns have no missing values. If you look carefully in the data dictionary, you'll notice that I changed the column named `database` in the CSV file to `databases` in the table. The reason is that `database` is a SQL reserved keyword, and it's unwise to use keywords as identifiers because it can lead to unintended consequences in queries or other functions.

The `startdat` and `enddat` columns contain dates, but we've set their data type to `varchar(10)` in the code because in the CSV file those columns include non-date values, and our import will fail if we try to use a `date` data type. In Chapter 9, you'll learn how to clean up cases like these. For now, those columns are fine as is.

After creating the table, we add indexes ❷ to columns we'll use for queries. This provides faster results when we search the column for a particular library. The `COPY` statement ❸ imports the data from a CSV file named *pls_fy2014_pupld14a.csv* using the file path you provide.

Creating the 2009 Library Data Table

Creating the table for the 2009 library data follows similar steps, as shown in Listing 8-2. Most ongoing surveys will have a handful of year-to-year changes because the makers of the survey either think of new questions or modify existing ones, so the included columns will be slightly different in this table. That's one reason the data providers create new tables instead of adding rows to a cumulative table. For example, the 2014 file has a `wifisess` column, which lists the annual number of Wi-Fi sessions the library provided, but this column doesn't exist in the 2009 data. The data dictionary for this survey year is at *https://www.imls.gov/sites/default/files/fy2009_pls_data_file_documentation.pdf*.

After you build this table, import the CSV file *pls_fy2009_pupld09a*. This file is also available to download along with all the book's resources at *https://www.nostarch.com/practicalSQL/*. When you've saved the file and added the correct file path to the `COPY` statement, execute the code in Listing 8-2:

```
CREATE TABLE pls_fy2009_pupld09a (
    stabr varchar(2) NOT NULL,
❶   fscskey varchar(6) CONSTRAINT fscskey2009_key PRIMARY KEY,
    libid varchar(20) NOT NULL,
    libname varchar(60) NOT NULL,
    address varchar(35) NOT NULL,
    city varchar(20) NOT NULL,
    zip varchar(5) NOT NULL,
    zip4 varchar(4) NOT NULL,
    cnty varchar(20) NOT NULL,
    --snip--
    fipsst varchar(2) NOT NULL,
    fipsco varchar(3) NOT NULL
);

❷ CREATE INDEX libname2009_idx ON pls_fy2009_pupld09a (libname);
CREATE INDEX stabr2009_idx ON pls_fy2009_pupld09a (stabr);
CREATE INDEX city2009_idx ON pls_fy2009_pupld09a (city);
CREATE INDEX visits2009_idx ON pls_fy2009_pupld09a (visits);

COPY pls_fy2009_pupld09a
FROM 'C:\YourDirectory\pls_fy2009_pupld09a.csv'
WITH (FORMAT CSV, HEADER);
```

Listing 8-2: Creating and filling the 2009 Public Libraries Survey table

We use `fscskey` as the primary key again ❶, and we create an index on the `libname` column ❷. Now, let's mine the two tables of library data from 2014 and 2009 to discover their stories.

Exploring the Libraries Data Using Aggregate Functions

Aggregate functions combine values from multiple rows and return a single result based on an operation on those values. For example, you might return the average of values with the `avg()` function, as you learned in Chapter 5. That's just one of many aggregate functions in SQL. Some are part of the SQL standard, and others are specific to PostgreSQL and other database managers. Most of the aggregate functions used in this chapter are part of standard SQL (a full list of PostgreSQL aggregates is at *https://www.postgresql.org/docs/current/static/functions-aggregate.html*).

In this section, we'll work through the library data using aggregates on single and multiple columns, and then explore how you can expand their use by grouping the results they return with values from additional columns.

Counting Rows and Values Using count()

After importing a dataset, a sensible first step is to make sure the table has the expected number of rows. For example, the IMLS documentation for the 2014 data says the file we imported has 9,305 rows, and the 2009 file has 9,299 rows. When we count the number of rows in those tables, the results should match those counts.

The `count()` aggregate function, which is part of the ANSI SQL standard, makes it easy to check the number of rows and perform other counting tasks. If we supply an asterisk as an input, such as `count(*)`, the asterisk acts as a wildcard, so the function returns the number of table rows regardless of whether they include `NULL` values. We do this in both statements in Listing 8-3:

```
SELECT count(*)
FROM pls_fy2014_pupld14a;

SELECT count(*)
FROM pls_fy2009_pupld09a;
```

Listing 8-3: Using `count()` for table row counts

Run each of the commands in Listing 8-3 one at a time to see the table row counts. For `pls_fy2014_pupld14a`, the result should be:

```
count
-----
 9305
```

And for `pls_fy2009_pupld09a`, the result should be:

```
count
-----
 9299
```

Both results match the number of rows we expected.

NOTE *You can also check row count using the pgAdmin interface, but it's clunky. Right-clicking the table name in pgAdmin's object browser and selecting* ***View Data*** ▸ ***View All Rows*** *executes a SQL query for all rows. Then, a pop-up message in the results pane shows the row count, but it disappears after a few seconds.*

Comparing the number of table rows to what the documentation says is important because it alerts us to issues, such as missing rows or even cases where we might have imported the wrong file.

Counting Values Present in a Column

To return the number of rows in a specific column that contain values, we supply the name of a column as input to `count()` rather than an asterisk. For example, if you scan the `CREATE TABLE` statements for both library tables closely, you'll notice that we omitted the `NOT NULL` constraint for the `salaries` column plus several others. The reason is that not every library agency reported salaries, and some rows have `NULL` values.

To count the number of rows in the salaries column from 2014 that have values, run the `count` function in Listing 8-4:

```
SELECT count(salaries)
FROM pls_fy2014_pupld14a;
```

Listing 8-4: Using count() for the number of values in a column

The result shows 5,983 rows have a value in `salaries`:

```
count
-----
 5983
```

This number is far lower than the number of rows that exist in the table. In the 2014 data, slightly less than two-thirds of the agencies reported salaries, and you'd want to note that fact when reporting any results of calculations performed on those columns. This check is important because the extent to which values are present in a column might influence your decision on whether to proceed with analysis at all. Checking with experts on the topic and digging deeper into the data is usually a good idea.

Counting Distinct Values in a Column

In Chapter 2, I covered the `DISTINCT` keyword, which is part of the SQL standard. When added after `SELECT` in a query, `DISTINCT` returns a list of unique values. We can use it to see unique values in one column, or we can see unique combinations of values from multiple columns. Another use of `DISTINCT` is to add it to the `count()` function, which causes the function to return a count of distinct values from a column.

Listing 8-5 shows two queries. The first counts all values in the 2014 table's `libname` column. The second does the same but includes `DISTINCT` in front of the column name. Run them both one at a time.

```
SELECT count(libname)
FROM pls_fy2014_pupld14a;

SELECT count(DISTINCT libname)
FROM pls_fy2014_pupld14a;
```

Listing 8-5: Using `count()` *for the number of distinct values in a column*

The first query returns a row count that matches the number of rows in the table that we found using Listing 8-3:

```
count
-----
 9305
```

That's good. We expect to have the library agency name listed in every row. But the second query returns a smaller number:

```
count
-----
 8515
```

The difference between the total count and the unduplicated count is about 800, which indicates that about 800 library agencies in the United States share the same name. As one example, nine library agencies are named `OXFORD PUBLIC LIBRARY` in the table, each one in a city named Oxford in different states, including Alabama, Connecticut, Kansas, and Pennsylvania, among others. We'll write a query to see combinations of distinct values later in this chapter, in the section "Aggregating Data Using GROUP BY" on page 120.

Finding Maximum and Minimum Values Using max() and min()

Knowing the largest and smallest numbers in a column is useful for a couple of reasons. First, it helps us get a sense of the scope of the values reported for a particular variable. Second, the functions used, `max()` and `min()`, can reveal unexpected issues with the data, which you'll find out now with the libraries data.

Both `max()` and `min()`work the same way: you use a `SELECT` statement followed by the function with the name of a column supplied. Listing 8-6 uses `max()` and `min()` on the 2014 table with the `visits` column as input. The `visits` column records the number of annual visits to the library agency and all of its branches. Run the code, and then we'll review the output.

```
SELECT max(visits), min(visits)
FROM pls_fy2014_pupld14a;
```

Listing 8-6: Finding the most and fewest visits using `max()` *and* `min()`

The query returns the following results:

```
max         min
--------    ---
17729020     -3
```

Well, that's interesting. The maximum value of more than 17.7 million is reasonable for a large city library system, but -3 as the minimum? On the surface, that result seems like a mistake, but it turns out that the creators of the library survey are employing a problematic yet common convention in data collection: using a negative number or some artificially high value as an indicator.

In this case, the survey creators used negative numbers to indicate the following conditions:

1. A value of -1 indicates a "nonresponse" to that question.
2. A value of -3 indicates "not applicable" and is used when a library agency has closed either temporarily or permanently.

We'll need to account for and exclude negative values as we explore the data, because summing a column and including the negative values will result in an incorrect total. We can do this using a WHERE clause to filter them. It's a good thing we discovered this issue now rather than later after spending a lot of time on deeper analysis!

NOTE *A better alternative for this negative value scenario is to use* NULL *in rows in* visits *where response data is absent, and then create a separate* visits_flag *column to hold codes explaining why. This technique separates number values from information about them.*

Aggregating Data Using GROUP BY

When you use the GROUP BY clause with aggregate functions, you can group results according to the values in one or more columns. This allows us to perform operations like sum() or count() for every state in our table or for every type of library agency.

Let's explore how using GROUP BY with aggregates works. On its own, GROUP BY, which is also part of standard ANSI SQL, eliminates duplicate values from the results, similar to DISTINCT. Listing 8-7 shows the GROUP BY clause in action:

```
SELECT stabr
FROM pls_fy2014_pupld14a
❶ GROUP BY stabr
ORDER BY stabr;
```

Listing 8-7: Using GROUP BY on the stabr column

The GROUP BY clause ❶ follows the FROM clause and includes the column name to group. In this case, we're selecting stabr, which contains the state abbreviation, and grouping by that same column. We then ORDER BY stabr as well so the grouped results are in alphabetical order. This will yield a result with unique state abbreviations from the 2014 table. Here's a portion of the results:

```
stabr
-----
AK
AL
AR
AS
AZ
CA
--snip--
WV
WY
```

Notice that there are no duplicates in the 56 rows returned. These standard two-letter postal abbreviations include the 50 states plus Washington, D.C., and several US territories, such as American Samoa and the Virgin Islands.

You're not limited to grouping just one column. In Listing 8-8, we use the GROUP BY clause on the 2014 data to specify the city and stabr columns for grouping:

```
SELECT city, stabr
FROM pls_fy2014_pupld14a
GROUP BY city, stabr
ORDER BY city, stabr;
```

Listing 8-8: Using GROUP BY on the stabr and city columns

The results get sorted by city and then by state, and the output shows unique combinations in that order:

```
city         stabr
----------   -----
ABBEVILLE    AL
ABBEVILLE    LA
ABBEVILLE    SC
ABBOTSFORD   WI
ABERDEEN     ID
ABERDEEN     SD
ABERNATHY    TX
--snip--
```

This grouping returns 9,088 rows, 217 fewer than the total table rows. The result indicates there are multiple occasions where the file includes more than one library agency for a particular city and state combination.

Combining GROUP BY with count()

If we combine `GROUP BY` with an aggregate function, such as `count()`, we can pull more descriptive information from our data. For example, we know 9,305 library agencies are in the 2014 table. We can get a count of agencies by state and sort them to see which states have the most. Listing 8-9 shows how:

```
❶ SELECT stabr, count(*)
  FROM pls_fy2014_pupld14a
❷ GROUP BY stabr
❸ ORDER BY count(*) DESC;
```

Listing 8-9: `GROUP BY` with `count()` on the `stabr` column

Unlike in earlier examples, we're now asking for the values in the `stabr` column and a count of those values. In the list of columns to query ❶, we specify `stabr` and the `count()` function with an asterisk as its input. As before, the asterisk causes `count()` to include `NULL` values. Also, when we select individual columns along with an aggregate function, we must include the columns in a `GROUP BY` clause ❷. If we don't, the database will return an error telling us to do so. The reason is that you can't group values by aggregating and have ungrouped column values in the same query.

To sort the results and have the state with the largest number of agencies at the top, we can `ORDER BY` the `count()` function ❸ in descending order using `DESC`.

Run the code in Listing 8-9. The results show New York, Illinois, and Texas as the states with the greatest number of library agencies in 2014:

```
stabr    count
-----    -----
NY         756
IL         625
TX         556
IA         543
PA         455
MI         389
WI         381
MA         370
--snip--
```

Remember that our table represents library agencies that serve a locality. Just because New York, Illinois, and Texas have the greatest number of library agencies doesn't mean they have the greatest number of outlets where you can walk in and peruse the shelves. An agency might have one central library only, or it might have no central libraries but 23 branches spread around a county. To count outlets, each row in the table also has values in the columns `centlib` and `branlib`, which record the number of central and branch libraries, respectively. To find totals, we would use `sum()` on both columns.

GROUP BY on Multiple Columns with count()

We can glean yet more information from our data by combining `GROUP BY` with `count()` and multiple columns. For example, the `stataddr` column in both tables contains a code indicating whether the agency's address changed in the last year. The values in `stataddr` are:

00 No change from last year

07 Moved to a new location

15 Minor address change

Listing 8-10 shows the code for counting the number of agencies in each state that moved, had a minor address change, or had no change using `GROUP BY` with `stabr` and `stataddr` and adding `count()`:

```
❶ SELECT stabr, stataddr, count(*)
  FROM pls_fy2014_pupld14a
❷ GROUP BY stabr, stataddr
❸ ORDER BY stabr ASC, count(*) DESC;
```

Listing 8-10: `GROUP BY` with `count()` of the `stabr` and `stataddr` columns

The key sections of the query are the column names and `count()` function after `SELECT` ❶ and making sure both columns are reflected in the `GROUP BY` clause ❷. The effect of grouping by two columns is that `count()` will show the number of unique combinations of `stabr` and `stataddr`.

To make the output easier to read, let's sort first by the state code in ascending order and then by the count in descending order ❸. Here are the results:

```
stabr    stataddr    count
-----    --------    -----
AK       00             70
AK       15             10
AK       07              5
AL       00            221
AL       07              3
AR       00             58
AS       00              1
AZ       00             91
--snip--
```

The first few rows of the results show that code `00` (no change in address) is the most common value for each state. We'd expect that because it's likely there are more library agencies that haven't changed address than those that have. The result helps assure us that we're analyzing the data in a sound way. If code `07` (moved to a new location) was the most frequent in each state, that would raise a question about whether we've written the query correctly or whether there's an issue with the data.

Revisiting sum() to Examine Library Visits

So far, we've combined grouping with aggregate functions, like `count()`, on columns within a single table to provide results grouped by a column's values. Now let's expand the technique to include grouping and aggregating across joined tables using the 2014 and 2009 libraries data. Our goal is to identify trends in library visits spanning that five-year period. To do this, we need to calculate totals using the `sum()` aggregate function.

Before we dig into these queries, let's address the issue of using the values `-3` and `-1` to indicate "not applicable" and "nonresponse." To prevent these negative numbers with no meaning as quantities from affecting the analysis, we'll filter them out using a `WHERE` clause to limit the queries to rows where values in `visits` are zero or greater.

Let's start by calculating the sum of annual visits to libraries from the individual 2014 and 2009 tables. Run each `SELECT` statement in Listing 8-11 separately:

```
SELECT sum(visits) AS visits_2014
FROM pls_fy2014_pupld14a
WHERE visits >= 0;

SELECT sum(visits) AS visits_2009
FROM pls_fy2009_pupld09a
WHERE visits >= 0;
```

Listing 8-11: Using `sum()` to total visits to libraries in 2014 and 2009

For 2014, visits totaled approximately 1.4 billion.

```
visits_2014
-----------
 1425930900
```

For 2009, visits totaled approximately 1.6 billion. We're onto something here, but it may not be good news. The trend seems to point downward with visits dropping about 10 percent from 2009 to 2014.

```
visits_2009
-----------
 1591799201
```

These queries sum overall visits. But from the row counts we ran earlier in the chapter, we know that each table contains a different number of library agencies: 9,305 in 2014 and 9,299 in 2009 due to agencies opening, closing, or merging. So, let's determine how the sum of visits will differ if we limit the analysis to library agencies that exist in both tables. We can do that by joining the tables, as shown in Listing 8-12:

```
❶ SELECT sum(pls14.visits) AS visits_2014,
         sum(pls09.visits) AS visits_2009
❷ FROM pls_fy2014_pupld14a pls14 JOIN pls_fy2009_pupld09a pls09
```

```
   ON pls14.fscskey = pls09.fscskey
❸ WHERE pls14.visits >= 0 AND pls09.visits >= 0;
```

Listing 8-12: Using sum() to total visits on joined 2014 and 2009 library tables

This query pulls together a few concepts we covered in earlier chapters, including table joins. At the top, we use the `sum()` aggregate function ❶ to total the `visits` columns from the 2014 and 2009 tables. When we join the tables on the tables' primary keys, we're declaring table aliases ❷ as we explored in Chapter 6. Here, we declare `pls14` as the alias for the 2014 table and `pls09` as the alias for the 2009 table to avoid having to write the lengthier full table names throughout the query.

Note that we use a standard `JOIN`, also known as an `INNER JOIN`. That means the query results will only include rows where the primary key values of both tables (the column `fscskey`) match.

Using the `WHERE` clause ❸, we exclude rows from either table that contain negative values in the `visits` column. As we did in Listing 8-11, we specify that the result should include only those rows where `visits` are greater than or equal to `0` in both tables. This will prevent the artificial negative values from impacting the sums.

Run the query. The results should look like this:

```
visits_2014   visits_2009
-----------   -----------
 1417299241    1585455205
```

The results are similar to what we found by querying the tables separately, although these totals are six to eight million smaller. The reason is that the query referenced only agencies with an `fscskey` in both tables. Still, the downward trend holds. We'll need to dig a little deeper to get the full story.

NOTE *Although we joined the tables on `fscskey`, it's entirely possible that some library agencies that appear in both tables merged or split between 2009 and 2014. A call to the IMLS asking about caveats for working with this data is a good idea.*

Grouping Visit Sums by State

Now that we know library visits dropped for the United States as a whole between 2009 and 2014, you might ask yourself, "Did every part of the country see a decrease, or did the degree of the trend vary by region?" We can answer this question by modifying our preceding query to `GROUP BY` the state code. Let's also use a percent-change calculation to compare the trend by state. Listing 8-13 contains the full code:

```
❶ SELECT pls14.stabr,
         sum(pls14.visits) AS visits_2014,
         sum(pls09.visits) AS visits_2009,
         round( (CAST(sum(pls14.visits) AS decimal(10,1)) - sum(pls09.visits)) /
```

```
❷                   sum(pls09.visits) * 100, 2 ) AS pct_change
  FROM pls_fy2014_pupld14a pls14 JOIN pls_fy2009_pupld09a pls09
  ON pls14.fscskey = pls09.fscskey
  WHERE pls14.visits >= 0 AND pls09.visits >= 0
❸ GROUP BY pls14.stabr
❹ ORDER BY pct_change DESC;
```

Listing 8-13: Using `GROUP BY` to track percent change in library visits by state

We follow the `SELECT` keyword with the `stabr` column ❶ from the 2014 table; that same column appears in the `GROUP BY` clause ❸. It doesn't matter which table's `stabr` column we use because we're only querying agencies that appear in both tables. After `SELECT`, we also include the now-familiar percent-change calculation you learned in Chapter 5, which gets the alias `pct_change` ❷ for readability. We end the query with an `ORDER BY` clause ❹, using the `pct_change` column alias.

When you run the query, the top of the results shows 10 states or territories with an increase in visits from 2009 to 2014. The rest of the results show a decline. Oklahoma, at the bottom of the ranking, had a 35 percent drop!

```
stabr    visits_2014    visits_2009    Pct. Chg.
-----    -----------    -----------    ---------
GU            103593          60763        70.49
DC           4230790        2944774        43.67
LA          17242110       15591805        10.58
MT           4582604        4386504         4.47
AL          17113602       16933967         1.06
AR          10762521       10660058         0.96
KY          19256394       19113478         0.75
CO          32978245       32782247         0.60
SC          18178677       18105931         0.40
SD           3899554        3890392         0.24
MA          42011647       42237888        -0.54
AK           3486955        3525093        -1.08
ID           8730670        8847034        -1.32
NH           7508751        7675823        -2.18
WY           3666825        3756294        -2.38
--snip--
RI           5259143        6612167       -20.46
NC          33952977       43111094       -21.24
PR            193279         257032       -24.80
GA          28891017       40922598       -29.40
OK          13678542       21171452       -35.39
```

This useful data should lead a data analyst to investigate what's driving the changes, particularly the largest ones. Data analysis can sometimes raise as many questions as it answers, but that's part of the process. It's always worth a phone call to a person with knowledge about the data to provide context for the results. Sometimes, they may have a very good explanation. Other times, an expert will say, "That doesn't sound right." That answer might send you back to the keeper of the data or the documentation to find out if you overlooked a code or a nuance with the data.

Filtering an Aggregate Query Using HAVING

We can refine our analysis by examining a subset of states and territories that share similar characteristics. With percent change in visits, it makes sense to separate large states from small states. In a small state like Rhode Island, one library closing could have a significant effect. A single closure in California might be scarcely noticed in a statewide count. To look at states with a similar volume in visits, we could sort the results by either of the `visits` columns, but it would be cleaner to get a smaller result set in our query.

To filter the results of aggregate functions, we need to use the `HAVING` clause that's part of standard ANSI SQL. You're already familiar with using `WHERE` for filtering, but aggregate functions, such as `sum()`, can't be used within a `WHERE` clause because they operate at the row level, and aggregate functions work across rows. The `HAVING` clause places conditions on groups created by aggregating. The code in Listing 8-14 modifies the query in Listing 8-13 by inserting the `HAVING` clause after `GROUP BY`:

```
SELECT pls14.stabr,
       sum(pls14.visits) AS visits_2014,
       sum(pls09.visits) AS visits_2009,
       round( (CAST(sum(pls14.visits) AS decimal(10,1)) - sum(pls09.visits)) /
                    sum(pls09.visits) * 100, 2 ) AS pct_change
FROM pls_fy2014_pupld14a pls14 JOIN pls_fy2009_pupld09a pls09
ON pls14.fscskey = pls09.fscskey
WHERE pls14.visits >= 0 AND pls09.visits >= 0
GROUP BY pls14.stabr
❶ HAVING sum(pls14.visits) > 50000000
ORDER BY pct_change DESC;
```

Listing 8-14: Using `HAVING` to filter the results of an aggregate query

In this case, we've set our query results to include only rows with a sum of visits in 2014 greater than 50 million. That's an arbitrary value I chose to show only the very largest states. Adding the `HAVING` clause ❶ reduces the number of rows in the output to just six. In practice, you might experiment with various values. Here are the results:

```
stabr   visits_2014   visits_2009   Pct. Chg.
-----   -----------   -----------   ---------
TX         72876601      78838400       -7.56
CA        162787836     182181408      -10.65
OH         82495138      92402369      -10.72
NY        106453546     119810969      -11.15
IL         72598213      82438755      -11.94
FL         73165352      87730886      -16.60
```

Each of the six states has experienced a decline in visits, but notice that the percent-change variation isn't as wide as in the full set of states and territories. Depending on what we learn from library experts, looking at the states with the most activity as a group might be helpful in describing trends, as would looking at other groupings. Think of a sentence or bullet point you might write that would say, "In the nation's largest states, visits decreased between 8 percent and 16 percent." You could write similar sentences about medium-sized states and small states.

Wrapping Up

If this chapter has inspired you to visit your local library and check out a couple of books, ask a librarian whether their branch has seen a rise or drop in visits over the last few years. Chances are, you can guess the answer now. In this chapter, you learned how to use standard SQL techniques to summarize data in a table by grouping values and using a handful of aggregate functions. By joining data sets spanning five years, you were able to compare summaries from each table to identify some interesting trends.

You also learned that data doesn't always come perfectly packaged. The use of negative values in columns as an indicator rather than as an actual numeric value forced us to filter out those rows. Unfortunately, datasets offer those kinds of challenges more often than not. In the next chapter, you'll learn techniques to clean up a dataset that has a number of issues. In subsequent chapters, you'll also discover more aggregate functions to help you find the stories in your data.

Try It Yourself

Put your grouping and aggregating skills to the test with these challenges:

1. We saw that library visits have declined recently in most places. But what is the pattern in the use of technology in libraries? Both the 2014 and 2009 library survey tables contain the columns `gpterms` (the number of internet-connected computers used by the public) and `pitusr` (uses of public internet computers per year). Modify the code in Listing 8-13 to calculate the percent change in the sum of each column over time. Watch out for negative values!
2. Both library survey tables contain a column called `obereg`, a two-digit Bureau of Economic Analysis Code that classifies each library agency according to a region of the United States, such as New England, Rocky Mountains, and so on. Just as we calculated the percent change in visits grouped by state, do the same to group percent changes in visits by US regions using `obereg`. Consult the survey documentation to find the meaning of each region code. For a bonus challenge, create a table with the `obereg` code as the primary key and the region name as text, and join it to the summary query to group by the region name rather than the code.
3. Thinking back to the types of joins you learned in Chapter 6, which join type will show you all the rows in both tables, including those without a match? Write such a query and add an `IS NULL` filter in a `WHERE` clause to show agencies not included in one or the other table.

9

INSPECTING AND MODIFYING DATA

If you asked me to propose a toast to a newly minted class of data analysts, I'd probably raise my glass and say, "May your data always be free of errors and may it always arrive perfectly structured!" Life would be ideal if these sentiments were feasible. In reality, you'll sometimes receive data in such a sorry state that it's hard to analyze without modifying it in some way. This is called *dirty data*, which is a general label for data with errors, missing values, or poor organization that make standard queries ineffective. When data is converted from one file type to another or when a column receives the wrong data type, information can be lost. Typos and spelling inconsistencies can also result in dirty data. Whatever the cause may be, dirty data is the bane of the data analyst.

In this chapter, you'll use SQL to clean up dirty data as well as perform other useful maintenance tasks. You'll learn how to examine data to assess its quality and how to modify data and tables to make analysis easier. But the techniques you'll learn will be useful for more than just cleaning data.

The ability to make changes to data and tables gives you options for updating or adding new information to your database as it becomes available, elevating your database from a static collection to a living record.

Let's begin by importing our data.

Importing Data on Meat, Poultry, and Egg Producers

For this example, we'll use a directory of US meat, poultry, and egg producers. The Food Safety and Inspection Service (FSIS), an agency within the US Department of Agriculture, compiles and updates this database every month. The FSIS is responsible for inspecting animals and food at more than 6,000 meat processing plants, slaughterhouses, farms, and the like. If inspectors find a problem, such as bacterial contamination or mislabeled food, the agency can issue a recall. Anyone interested in agriculture business, food supply chain, or outbreaks of foodborne illnesses will find the directory useful. Read more about the agency on its site at *https://www.fsis.usda.gov/*.

The file we'll use comes from the directory's page on *https://www.data.gov*, a website run by the US federal government that catalogs thousands of datasets from various federal agencies (*https://catalog.data.gov/dataset/meat-poultry-and-egg-inspection-directory-by-establishment-name/*). We'll examine the original data as it was available for download with the exception of the ZIP Codes column. I'll explain why later. You'll find the data in the file *MPI_Directory_by_Establishment_Name.csv* along with other resources for this book at *https://www.nostarch.com/practicalSQL/*.

To import the file into PostgreSQL, use the code in Listing 9-1 to create a table called `meat_poultry_egg_inspect` and `COPY` the CSV file into the table. As you've done in previous examples, use pgAdmin to connect to your `analysis` database, and then open the Query Tool to run the code. Remember to change the path in the `COPY` statement to reflect the location of your CSV file.

```
CREATE TABLE meat_poultry_egg_inspect (
❶    est_number varchar(50) CONSTRAINT est_number_key PRIMARY KEY,
    company varchar(100),
    street varchar(100),
    city varchar(30),
    st varchar(2),
    zip varchar(5),
    phone varchar(14),
    grant_date date,
❷    activities text,
    dbas text
);

❸ COPY meat_poultry_egg_inspect
FROM 'C:\YourDirectory\MPI_Directory_by_Establishment_Name.csv'
WITH (FORMAT CSV, HEADER, DELIMITER ',');

❹ CREATE INDEX company_idx ON meat_poultry_egg_inspect (company);
```

Listing 9-1: Importing the FSIS Meat, Poultry, and Egg Inspection Directory

The meat_poultry_egg_inspect table has 10 columns. We add a natural primary key constraint to the est_number column ❶, which contains a unique value for each row that identifies the establishment. Most of the remaining columns relate to the company's name and location. You'll use the activities column ❷, which describes activities at the company, in the Try It Yourself exercise at the end of this chapter. We set the activities and dbas columns to text, a data type that in PostgreSQL affords us up to 1GB of characters, because some of the strings in the columns are thousands of characters long. We import the CSV file ❸ and then create an index on the company column ❹ to speed up searches for particular companies.

For practice, let's use the count() aggregate function introduced in Chapter 8 to check how many rows are in the meat_poultry_egg_inspect table:

```
SELECT count(*) FROM meat_poultry_egg_inspect;
```

The result should show 6,287 rows. Now let's find out what the data contains and determine whether we can glean useful information from it as is or if we need to modify it in some way.

Interviewing the Dataset

Interviewing data is my favorite part of analysis. We interview a dataset to discover its details: what it holds, what questions it can answer, and how suitable it is for our purposes, the same way a job interview reveals whether a candidate has the skills required for the position.

The aggregate queries you learned in Chapter 8 are a useful interviewing tool because they often expose the limitations of a dataset or raise questions you may want to ask before reaching conclusions in your analysis and assuming the validity of your findings.

For example, the meat_poultry_egg_inspect table's rows describe food producers. At first glance, we might assume that each company in each row operates at a distinct address. But it's never safe to assume in data analysis, so let's check using the code in Listing 9-2:

```
SELECT company,
       street,
       city,
       st,
       count(*) AS address_count
FROM meat_poultry_egg_inspect
GROUP BY company, street, city, st
HAVING count(*) > 1
ORDER BY company, street, city, st;
```

Listing 9-2: Finding multiple companies at the same address

Here, we group companies by unique combinations of the company, street, city, and st columns. Then we use count(*), which returns the number of rows for each combination of those columns and give it the alias address_count. Using the HAVING clause introduced in Chapter 8, we filter the results to show only cases where more than one row has the same combination of values. This should return all duplicate addresses for a company.

The query returns 23 rows, which means there are close to two dozen cases where the same company is listed multiple times at the same address:

```
company                   street                     city         st    address_count
-----------------------   -----------------------    ----------   --    -------------
Acre Station Meat Farm    17076 Hwy 32 N             Pinetown     NC                2
Beltex Corporation        3801 North Grove Street    Fort Worth   TX                2
Cloverleaf Cold Storage   111 Imperial Drive         Sanford      NC                2
--snip--
```

This is not necessarily a problem. There may be valid reasons for a company to appear multiple times at the same address. For example, two types of processing plants could exist with the same name. On the other hand, we may have found data entry errors. Either way, it's sound practice to eliminate concerns about the validity of a dataset before relying on it, and the result should prompt us to investigate individual cases before we draw conclusions. However, this dataset has other issues that we need to look at before we can get meaningful information from it. Let's work through a few examples.

Checking for Missing Values

Let's start checking for missing values by asking a basic question: how many of the meat, poultry, and egg processing companies are in each state? Finding out whether we have values from all states and whether any rows are missing a state code will serve as another useful check on the data. We'll use the aggregate function count() along with GROUP BY to determine this, as shown in Listing 9-3:

```
SELECT st,
       count(*) AS st_count
FROM meat_poultry_egg_inspect
GROUP BY st
ORDER BY st;
```

Listing 9-3: Grouping and counting states

The query is a simple count similar to the examples in Chapter 8. When you run the query, it tallies the number of times each state postal code (st) appears in the table. Your result should include 57 rows, grouped by the state postal code in the column st. Why more than the 50 US states? Because the data includes Puerto Rico and other unincorporated US territories, such as Guam and American Samoa. Alaska (AK) is at the top of the results with a count of 17 establishments:

```
st    st_count
--    --------
AK          17
AL          93
```

```
AR         87
AS          1
--snip--
WA        139
WI        184
WV         23
WY          1
            3
```

However, the row at the bottom of the list has a count of `3` and a `NULL` value in the `st_count` column. To find out what this means, let's query the rows where the `st` column has `NULL` values.

NOTE *Depending on the database implementation,* `NULL` *values will either appear first or last in a sorted column. In PostgreSQL, they appear last by default. The ANSI SQL standard doesn't specify one or the other, but it lets you add* `NULLS FIRST` *or* `NULLS LAST` *to an* `ORDER BY` *clause to specify a preference. For example, to make* `NULL` *values appear first in the preceding query, the clause would read* `ORDER BY st NULLS FIRST`.

In Listing 9-4, we use the technique covered in the Chapter 6 section "Using NULL to Find Rows with Missing Values" on page 67, adding a `WHERE` clause with the `st` column and the `IS NULL` keywords to find which rows are missing a state code:

```
SELECT est_number,
       company,
       city,
       st,
       zip
FROM meat_poultry_egg_inspect
WHERE st IS NULL;
```

Listing 9-4: Using `IS NULL` *to find missing values in the* `st` *column*

This query returns three rows that don't have a value in the `st` column:

```
est_number          company                            city     st    zip
-----------------   -------------------------------    ------   --    -----
V18677A             Atlas Inspection, Inc.             Blaine         55449
M45319+P45319       Hall-Namie Packing Company, Inc                   36671
M263A+P263A+V263A   Jones Dairy Farm                                  53538
```

If we want an accurate count of establishments per state, these missing values would lead to an incorrect result. To find the source of this dirty data, it's worth making a quick visual check of the original file downloaded from *https://www.data.gov/*. Unless you're working with files in the gigabyte range, you can usually open a CSV file in a text editor and search for the row. If you're working with larger files, you might be able to examine the source data using utilities such as `grep` (on Linux and Mac) or `findstr` (on

Windows). In this case, a visual check confirms that, indeed, there was no state listed in those rows in the CSV file, so the error is organic to the data, not one introduced during import.

In our interview of the data so far, we've discovered that we'll need to add missing values to the `st` column to clean up this table. Let's look at what other issues exist in our dataset and make a list of cleanup tasks.

Checking for Inconsistent Data Values

Inconsistent data is another factor that can hamper our analysis. We can check for inconsistently entered data within a column by using `GROUP BY` with `count()`. When you scan the unduplicated values in the results, you might be able to spot variations in the spelling of names or other attributes.

For example, many of the 6,200 companies in our table are multiple locations owned by a few multinational food corporations, such as Cargill and Tyson Foods. To find out how many locations each company owns, we would try to count the values in the `company` column. Let's see what happens when we do, using the SQL in Listing 9-5:

```
SELECT company,
       count(*) AS company_count
FROM meat_poultry_egg_inspect
GROUP BY company
ORDER BY company ASC;
```

Listing 9-5: Using `GROUP BY` and `count()` to find inconsistent company names

Scrolling through the results reveals a number of cases in which a company's name is spelled several different ways. For example, notice the entries for the Armour-Eckrich brand:

```
company                          company_count
----------------------------     -------------
--snip--
Armour - Eckrich Meats, LLC                  1
Armour-Eckrich Meats LLC                     3
Armour-Eckrich Meats, Inc.                   1
Armour-Eckrich Meats, LLC                    2
--snip--
```

At least four different spellings are shown for seven establishments that are likely owned by the same company. If we later perform any aggregation by company, it would help to standardize the names so all of the items counted or summed are grouped properly. Let's add that to our list of items to fix.

Checking for Malformed Values Using length()

It's a good idea to check for unexpected values in a column that should be consistently formatted. For example, each entry in the `zip` column in the `meat_poultry_egg_inspect` table should be formatted in the style of US ZIP Codes with five digits. However, that's not what is in our dataset.

Solely for the purpose of this example, I replicated an error I've committed before. When I converted the original Excel file to a CSV file, I stored the ZIP Code in the "General" number format in the spreadsheet instead of as a text value. By doing so, any ZIP Code that begins with a zero, such as 07502 for Paterson, NJ, lost the leading zero because an integer can't start with a zero. As a result, 07502 appears in the table as `7502`. (You can make this error in a variety of ways, including by copying and pasting data into Excel columns set to "General." After being burned a few times, I learned to take extra caution with numbers that should be formatted as text.)

My deliberate error appears when we run the code in Listing 9-6. The example introduces `length()`, a *string function* that counts the number of characters in a string. We combine `length()` with `count()` and `GROUP BY` to determine how many rows have five characters in the `zip` field and how many have a value other than five. To make it easy to scan the results, we use `length()` in the `ORDER BY` clause.

```
SELECT length(zip),
       count(*) AS length_count
FROM meat_poultry_egg_inspect
GROUP BY length(zip)
ORDER BY length(zip) ASC;
```

Listing 9-6: Using `length()` and `count()` to test the `zip` column

The results confirm the formatting error. As you can see, `496` of the ZIP Codes are four characters long, and `86` are three characters long, which means these numbers originally had two leading zeroes that my conversion erroneously eliminated:

```
length    length_count
------    ------------
     3              86
     4             496
     5            5705
```

Using the `WHERE` clause, we can check the details of the results to see which states these shortened ZIP Codes correspond to, as shown in Listing 9-7:

```
SELECT st,
       count(*) AS st_count
FROM meat_poultry_egg_inspect
❶ WHERE length(zip) < 5
GROUP BY st
ORDER BY st ASC;
```

Listing 9-7: Filtering with `length()` to find short `zip` values

The `length()` function inside the `WHERE` clause ❶ returns a count of rows where the ZIP is less than five characters for each state code. The result is what we would expect. The states are largely in the Northeast region of the United States where ZIP Codes often start with a zero:

```
st    st_count
--    --------
CT          55
MA         101
ME          24
NH          18
NJ         244
PR          84
RI          27
VI           2
VT          27
```

Obviously, we don't want this error to persist, so we'll add it to our list of items to correct. So far, we need to correct the following issues in our dataset:

1. Missing values for three rows in the `st` column
2. Inconsistent spelling of at least one company's name
3. Inaccurate ZIP Codes due to file conversion

We'll look at how to use SQL to fix these issues, but first you need to know what to do when your data fails the interview.

WHEN TO TOSS YOUR DATA

If your interview of the data reveals too many missing values or values that defy common sense—such as numbers ranging in the billions when you expected thousands—it's time to reevaluate its use. The data may not be reliable enough to serve as the foundation of your analysis.

If you suspect as much, the first step is to revisit the original data file. Make sure you imported it correctly and that values in all the source columns are located in the same columns in the table. You might need to open the original spreadsheet or CSV file and do a visual comparison. The second step is to call the agency or company that produced the data to confirm what you see and seek an explanation. You might also ask for advice from others who have used the same data.

More than once I've had to toss a dataset after determining that it was poorly assembled or simply incomplete. Sometimes, the amount of work required to make a dataset usable undermines its usefulness. These situations require you to make a tough judgment call. But it's better to start over or find an alternative than to use bad data that can lead to faulty conclusions.

Modifying Tables, Columns, and Data

Almost nothing in a database, from tables to columns and the data types and values they contain, is set in concrete after it's created. As your needs change, you can add columns to a table, change data types on existing columns, and edit values. Fortunately, you can use SQL to modify, delete, or add to existing data and structures. Given the issues we discovered in the `meat_poultry_egg_inspect` table, being able to modify our database will come in handy.

To make changes to our database, we'll use two SQL commands: the first command, `ALTER TABLE`, is part of the ANSI SQL standard and provides options to `ADD COLUMN`, `ALTER COLUMN`, and `DROP COLUMN`, among others. Typically, PostgreSQL and other databases include implementation-specific extensions to `ALTER TABLE` that provide an array of options for managing database objects (see *https://www.postgresql.org/docs/current/static/sql-altertable.html/*). For our exercises, we'll stick with the core options.

The second command, `UPDATE`, also included in the SQL standard, allows you to change values in a table's columns. You can supply criteria using the `WHERE` clause to choose which rows to update.

Let's explore the basic syntax and options for both commands, and then use them to fix the issues in our dataset.

Modifying Tables with ALTER TABLE

We can use the `ALTER TABLE` statement to modify the structure of tables. The following examples show the syntax for common operations that are part of standard ANSI SQL. The code for adding a column to a table looks like this:

```
ALTER TABLE table ADD COLUMN column data_type;
```

Similarly, we can remove a column with the following syntax:

```
ALTER TABLE table DROP COLUMN column;
```

To change the data type of a column, we would use this code:

```
ALTER TABLE table ALTER COLUMN column SET DATA TYPE data_type;
```

Adding a `NOT NULL` constraint to a column will look like the following:

```
ALTER TABLE table ALTER COLUMN column SET NOT NULL;
```

Note that in PostgreSQL and some other systems, adding a constraint to the table causes all rows to be checked to see whether they comply with the constraint. If the table has millions of rows, this could take a while.

Removing the `NOT NULL` constraint looks like this:

```
ALTER TABLE table ALTER COLUMN column DROP NOT NULL;
```

When you execute an ALTER TABLE statement with the placeholders filled in, you should see a message that reads ALTER TABLE in the pgAdmin output screen. If an operation violates a constraint or if you attempt to change a column's data type and the existing values in the column won't conform to the new data type, PostgreSQL returns an error. But PostgreSQL won't give you any warning about deleting data when you drop a column, so use extra caution before dropping a column.

Modifying Values with UPDATE

The UPDATE statement modifies the data in a column in all rows or in a subset of rows that meet a condition. Its basic syntax, which would update the data in every row in a column, follows this form:

```
UPDATE table
SET column = value;
```

We first pass UPDATE the name of the table to update, and then pass the SET clause the column that contains the values to change. The new *value* to place in the column can be a string, number, the name of another column, or even a query or expression that generates a value. We can update values in multiple columns at a time by adding additional columns and source values, and separating each column and value statement with a comma:

```
UPDATE table
SET column_a = value,
    column_b = value;
```

To restrict the update to particular rows, we add a WHERE clause with some criteria that must be met before the update can happen:

```
UPDATE table
SET column = value
WHERE criteria;
```

We can also update one table with values from another table. Standard ANSI SQL requires that we use a *subquery*, a query inside a query, to specify which values and rows to update:

```
UPDATE table
SET column = (SELECT column
             FROM table_b
             WHERE table.column = table_b.column)
WHERE EXISTS (SELECT column
              FROM table_b
              WHERE table.column = table_b.column);
```

The value portion of the SET clause is a subquery, which is a SELECT statement inside parentheses that generates the values for the update. Similarly, the WHERE EXISTS clause uses a SELECT statement to generate values that serve as the filter for the update. If we didn't use this clause, we might inadvertently set some values to NULL without planning to. (If this syntax looks somewhat complicated, that's okay. I'll cover subqueries in detail in Chapter 12.)

Some database managers offer additional syntax for updating across tables. PostgreSQL supports the ANSI standard but also a simpler syntax using a FROM clause for updating values across tables:

```
UPDATE table
SET column = table_b.column
FROM table_b
WHERE table.column = table_b.column;
```

When you execute an UPDATE statement, PostgreSQL returns a message stating UPDATE along with the number of rows affected.

Creating Backup Tables

Before modifying a table, it's a good idea to make a copy for reference and backup in case you accidentally destroy some data. Listing 9-8 shows how to use a variation of the familiar CREATE TABLE statement to make a new table based on the existing data and structure of the table we want to duplicate:

```
CREATE TABLE meat_poultry_egg_inspect_backup AS
SELECT * FROM meat_poultry_egg_inspect;
```

Listing 9-8: Backing up a table

After running the CREATE TABLE statement, the result should be a pristine copy of your table with the new specified name. You can confirm this by counting the number of records in both tables with one query:

```
SELECT
    (SELECT count(*) FROM meat_poultry_egg_inspect) AS original,
    (SELECT count(*) FROM meat_poultry_egg_inspect_backup) AS backup;
```

The results should return a count of 6,287 from both tables, like this:

```
original    backup
--------    ------
    6287      6287
```

If the counts match, you can be sure your backup table is an exact copy of the structure and contents of the original table. As an added measure and for easy reference, we'll use ALTER TABLE to make copies of column data within the table we're updating.

NOTE *Indexes are not copied when creating a table backup using the* CREATE TABLE *statement. If you decide to run queries on the backup, be sure to create a separate index on that table.*

Restoring Missing Column Values

Earlier in this chapter, the query in Listing 9-4 revealed that three rows in the meat_poultry_egg_inspect table don't have a value in the st column:

```
est_number           company                            city     st   zip
-----------------    -------------------------------    ------   --   -----
V18677A              Atlas Inspection, Inc.             Blaine        55449
M45319+P45319        Hall-Namie Packing Company, Inc                  36671
M263A+P263A+V263A    Jones Dairy Farm                                 53538
```

To get a complete count of establishments in each state, we need to fill those missing values using an UPDATE statement.

Creating a Column Copy

Even though we've backed up this table, let's take extra caution and make a copy of the st column within the table so we still have the original data if we make some dire error somewhere! Let's create the copy and fill it with the existing st column values using the SQL in Listing 9-9:

```
❶ ALTER TABLE meat_poultry_egg_inspect ADD COLUMN st_copy varchar(2);

  UPDATE meat_poultry_egg_inspect
❷ SET st_copy = st;
```

Listing 9-9: Creating and filling the st_copy column with ALTER TABLE and UPDATE

The ALTER TABLE statement ❶ adds a column called st_copy using the same varchar data type as the original st column. Next, the UPDATE statement's SET clause ❷ fills our newly created st_copy with the values in column st. Because we don't specify any criteria using a WHERE clause, values in every row are updated, and PostgreSQL returns the message UPDATE 6287. Again, it's worth noting that on a very large table, this operation could take some time and also substantially increase the table's size. Making a column copy in addition to a table backup isn't entirely necessary, but if you're the patient, cautious type, it can be worthwhile.

We can confirm the values were copied properly with a simple SELECT query on both columns, as in Listing 9-10:

```
SELECT st,
       st_copy
FROM meat_poultry_egg_inspect
ORDER BY st;
```

Listing 9-10: Checking values in the st and st_copy columns

The SELECT query returns 6,287 rows showing both columns holding values except the three rows with missing values:

```
st    st_copy
--    -------
AK    AK
AK    AK
AK    AK
AK    AK
--snip--
```

Now, with our original data safely stored in the st_copy column, we can update the three rows with missing state codes. This is now our backup, so if something goes drastically wrong while we're updating the missing data in the original column, we can easily copy the original data back in. I'll show you how after we apply the first updates.

Updating Rows Where Values Are Missing

To update those rows missing values, we first find the values we need with a quick online search: Atlas Inspection is located in Nebraska; Hall-Namie Packing is in Alabama; and Jones Dairy is in Wisconsin. Add those states to the appropriate rows using the code in Listing 9-11:

```
UPDATE meat_poultry_egg_inspect
SET st = 'NE'
❶ WHERE est_number = 'V18677A';

UPDATE meat_poultry_egg_inspect
SET st = 'AL'
WHERE est_number = 'M45319+P45319';

UPDATE meat_poultry_egg_inspect
SET st = 'WI'
WHERE est_number = 'M263A+P263A+V263A';
```

Listing 9-11: Updating the st column for three establishments

Because we want each UPDATE statement to affect a single row, we include a WHERE clause ❶ for each that identifies the company's unique est_number, which is the table's primary key. When we run each query, PostgreSQL responds with the message UPDATE 1, showing that only one row was updated for each query.

If we rerun the code in Listing 9-4 to find rows where st is NULL, the query should return nothing. Success! Our count of establishments by state is now complete.

Restoring Original Values

What happens if we botch an update by providing the wrong values or updating the wrong rows? Because we've backed up the entire table and the st column within the table, we can easily copy the data back from either location. Listing 9-12 shows the two options.

```
❶ UPDATE meat_poultry_egg_inspect
  SET st = st_copy;

❷ UPDATE meat_poultry_egg_inspect original
  SET st = backup.st
  FROM meat_poultry_egg_inspect_backup backup
  WHERE original.est_number = backup.est_number;
```

Listing 9-12: Restoring original st column values

To restore the values from the backup column in meat_poultry_egg_inspect you created in Listing 9-9, run an UPDATE query ❶ that sets st to the values in st_copy. Both columns should again have the identical original values. Alternatively, you can create an UPDATE ❷ that sets st to values in the st column from the meat_poultry_egg_inspect_backup table you made in Listing 9-8.

Updating Values for Consistency

In Listing 9-5 we discovered several cases where a single company's name was entered inconsistently. If we want to aggregate data by company name, such inconsistencies will hinder us from aggregating information by name.

Here are the spelling variations of Armour-Eckrich Meats in Listing 9-5:

```
--snip--
 Armour - Eckrich Meats, LLC     |     1
 Armour-Eckrich Meats LLC        |     3
 Armour-Eckrich Meats, Inc.      |     1
 Armour-Eckrich Meats, LLC       |     2
 --snip--
```

We can standardize the spelling of this company's name by using an UPDATE statement. To protect our data, we'll create a new column for the standardized spellings, copy the names in company into the new column, and work in the new column to avoid tampering with the original data. Listing 9-13 has the code for both actions:

```
ALTER TABLE meat_poultry_egg_inspect ADD COLUMN company_standard varchar(100);

UPDATE meat_poultry_egg_inspect
SET company_standard = company;
```

Listing 9-13: Creating and filling the company_standard column

Now, let's say we want any name in company that contains the string Armour to appear in company_standard as Armour-Eckrich Meats. (This assumes we've checked all entries containing Armour and want to standardize them.) We can update all the rows matching the string `Armour` by using a `WHERE` clause. Run the two statements in Listing 9-14:

```
UPDATE meat_poultry_egg_inspect
SET company_standard = 'Armour-Eckrich Meats'
❶ WHERE company LIKE 'Armour%';

SELECT company, company_standard
FROM meat_poultry_egg_inspect
WHERE company LIKE 'Armour%';
```

Listing 9-14: Use `UPDATE` to modify field values that match a string

The important piece of this query is the `WHERE` clause that uses the `LIKE` keyword ❶ that was introduced with filtering in Chapter 2. Including the wildcard syntax `%` at the end of the string `Armour` updates all rows that start with those characters regardless of what comes after them. The clause lets us target all the varied spellings used for the company's name. The `SELECT` statement in Listing 9-14 returns the results of the updated `company_standard` column next to the original `company` column:

```
company                        company_standard
---------------------------    --------------------
Armour-Eckrich Meats LLC       Armour-Eckrich Meats
Armour - Eckrich Meats, LLC    Armour-Eckrich Meats
Armour-Eckrich Meats LLC       Armour-Eckrich Meats
Armour-Eckrich Meats LLC       Armour-Eckrich Meats
Armour-Eckrich Meats, Inc.     Armour-Eckrich Meats
Armour-Eckrich Meats, LLC      Armour-Eckrich Meats
Armour-Eckrich Meats, LLC      Armour-Eckrich Meats
```

The values for Armour-Eckrich in `company_standard` are now standardized with consistent spelling. If we want to standardize additional company names in the table, we would create an `UPDATE` statement for each case. Most likely, we would also keep the original `company` column for reference.

Repairing ZIP Codes Using Concatenation

Our final fix repairs values in the `zip` column that lost leading zeroes as the result of my deliberate data faux pas. For companies in Puerto Rico and the Virgin Islands, we need to restore two leading zeroes to the values in `zip` because they're the only locations in the United States where ZIP Codes start with two zeros. Then, for the other states, located mostly in New England, we'll restore a single leading zero.

We'll use `UPDATE` again but this time in conjunction with the double-pipe *string operator* `||`, which performs *concatenation*. Concatenation combines two or more string or non-string values into one. For example, inserting `||` between two strings `abc` and `123` results in `abc123`. The double-pipe operator is a SQL standard for concatenation supported by PostgreSQL. You can use it in many contexts, such as `UPDATE` queries and `SELECT`, to provide custom output from existing as well as new data.

First, Listing 9-15 makes a backup copy of the `zip` column in the same way we made a backup of the `st` column earlier:

```
ALTER TABLE meat_poultry_egg_inspect ADD COLUMN zip_copy varchar(5);

UPDATE meat_poultry_egg_inspect
SET zip_copy = zip;
```

Listing 9-15: Creating and filling the `zip_copy` column

Next, we use the code in Listing 9-16 to perform the first update:

```
  UPDATE meat_poultry_egg_inspect
❶ SET zip = '00' || zip
❷ WHERE st IN('PR','VI') AND length(zip) = 3;
```

Listing 9-16: Modify codes in the `zip` column missing two leading zeros

We use `SET` to set the `zip` column ❶ to a value that is the result of the concatenation of the string `00` and the existing content of the `zip` column. We limit the `UPDATE` to only those rows where the `st` column has the state codes `PR` and `VI` ❷ using the `IN` comparison operator from Chapter 2 and add a test for rows where the length of `zip` is `3`. This entire statement will then only update the `zip` values for Puerto Rico and the Virgin Islands. Run the query; PostgreSQL should return the message `UPDATE 86`, which is the number of rows we expect to change based on our earlier count in Listing 9-6.

Let's repair the remaining ZIP Codes using a similar query in Listing 9-17:

```
UPDATE meat_poultry_egg_inspect
SET zip = '0' || zip
WHERE st IN('CT','MA','ME','NH','NJ','RI','VT') AND length(zip) = 4;
```

Listing 9-17: Modify codes in the `zip` column missing one leading zero

PostgreSQL should return the message `UPDATE 496`. Now, let's check our progress. Earlier in the chapter, when we aggregated rows in the `zip` column by length, we found `86` rows with three characters and `496` with four:

```
length    count
------    -----
     3       86
     4      496
     5     5705
```

Using the same query in Listing 9-6 now returns a more desirable result: all the rows have a five-digit ZIP Code.

```
length    count
------    -----
     5     6287
```

In this example we used concatenation, but you can employ additional SQL string functions to modify data with `UPDATE` by changing words from uppercase to lowercase, trimming unwanted spaces, replacing characters in a string, and more. I'll discuss additional string functions in Chapter 13 when we consider advanced techniques for working with text.

Updating Values Across Tables

Earlier in "Modifying Values with UPDATE" on page 138, I showed the standard ANSI SQL and PostgreSQL-specific syntax for updating values in one table based on values in another. This syntax is particularly valuable in a relational database where primary keys and foreign keys establish table relationships. It's also useful when data in one table may be necessary context for updating values in another.

For example, let's say we're setting an inspection date for each of the companies in our table. We want to do this by US regions, such as Northeast, Pacific states, and so on, but those regional designations don't exist in our table. However, they *do* exist in another table in our database that also contains matching `st` state codes. This means we can use that other table as part of our `UPDATE` statement to provide the necessary information. Let's begin with the New England region to see how this works.

Enter the code in Listing 9-18, which contains the SQL to create a `state_regions` table, and fill the table with data:

```
CREATE TABLE state_regions (
    st varchar(2) CONSTRAINT st_key PRIMARY KEY,
    region varchar(20) NOT NULL
);

COPY state_regions
FROM 'C:\YourDirectory\state_regions.csv'
WITH (FORMAT CSV, HEADER, DELIMITER ',');
```

Listing 9-18: Creating and filling a `state_regions` table

We'll create two columns in a `state_regions` table: one containing the two-character state code `st` and the other containing the `region` name. We set the primary key constraint to the `st` column, which holds a unique `st_key` value to identify each state. In the data you're importing, each state is present and assigned to a US Census region, and territories outside the United States are labeled as outlying areas. We'll update the table one region at a time.

Next, let's return to the meat_poultry_egg_inspect table, add a column for inspection dates, and then fill in that column with the New England states. Listing 9-19 shows the code:

```
ALTER TABLE meat_poultry_egg_inspect ADD COLUMN inspection_date date;

❶ UPDATE meat_poultry_egg_inspect inspect
❷ SET inspection_date = '2019-12-01'
❸ WHERE EXISTS (SELECT state_regions.region
                FROM state_regions
                WHERE inspect.st = state_regions.st
                      AND state_regions.region = 'New England');
```

Listing 9-19: Adding and updating an inspection_date column

The ALTER TABLE statement creates the inspection_date column in the meat_poultry_egg_inspect table. In the UPDATE statement, we start by naming the table using an alias of inspect to make the code easier to read ❶. Next, the SET clause assigns a date value of 2019-12-01 to the new inspection_date column ❷. Finally, the WHERE EXISTS clause includes a subquery that connects the meat_poultry_egg_inspect table to the state_regions table we created in Listing 9-18 and specifies which rows to update ❸. The subquery (in parentheses, beginning with SELECT) looks for rows in the state_regions table where the region field matches the string New England. At the same time, it joins the meat_poultry_egg_inspect table with the state_regions table using the st column from both tables. In effect, the query is telling the database to find all the st codes that correspond to the New England region and use those codes to filter the update.

When you run the code, you should receive a message of UPDATE 252, which is the number of companies in New England. You can use the code in Listing 9-20 to see the effect of the change:

```
SELECT st, inspection_date
FROM meat_poultry_egg_inspect
GROUP BY st, inspection_date
ORDER BY st;
```

Listing 9-20: Viewing updated inspection_date values

The results should show the updated inspection dates for all New England companies. The top of the output shows Connecticut has received a date, for example, but states outside New England remain NULL because we haven't updated them yet:

```
st    inspection_date
--    ---------------
AK
AL
AR
AS
AZ
CA
```

```
CO
CT    2019-12-01
DC
--snip--
```

To fill in dates for additional regions, substitute a different region for `New England` in Listing 9-19 and rerun the query.

Deleting Unnecessary Data

The most irrevocable way to modify data is to remove it entirely. SQL includes options to remove rows and columns from a table along with options to delete an entire table or database. We want to perform these operations with caution, removing only data or tables we don't need. Without a backup, the data is gone for good.

NOTE *It's easy to exclude unwanted data in queries using a* `WHERE` *clause, so decide whether you truly need to delete the data or can just filter it out. Cases where deleting may be the best solution include data with errors or data imported incorrectly.*

In this section, we'll use a variety of SQL statements to delete unnecessary data. For removing rows from a table, we'll use the `DELETE FROM` statement. To remove a column from a table, we'll use `ALTER TABLE`. And to remove a whole table from the database, we'll use the `DROP TABLE` statement.

Writing and executing these statements is fairly simple, but doing so comes with a caveat. If deleting rows, a column, or a table would cause a violation of a constraint, such as the foreign key constraint covered in Chapter 7, you need to deal with that constraint first. That might involve removing the constraint, deleting data in another table, or deleting another table. Each case is unique and will require a different way to work around the constraint.

Deleting Rows from a Table

Using `DELETE FROM`, we can remove all rows from a table, or we can use a `WHERE` clause to delete only the portion that matches an expression we supply. To delete all rows from a table, use the following syntax:

```
DELETE FROM table_name;
```

If your table has a large number of rows, it might be faster to erase the table and create a fresh version using the original `CREATE TABLE` statement. To erase the table, use the `DROP TABLE` command discussed in the later section "Deleting a Table from a Database" on page 148.

To remove only selected rows, add a `WHERE` clause along with the matching value or pattern to specify which ones you want to delete:

```
DELETE FROM table_name WHERE expression;
```

For example, if we want our table of meat, poultry, and egg processors to include only establishments in the 50 US states, we can remove the companies in Puerto Rico and the Virgin Islands from the table using the code in Listing 9-21:

```
DELETE FROM meat_poultry_egg_inspect
WHERE st IN('PR','VI');
```

Listing 9-21: Delete rows matching an expression

Run the code; PostgreSQL should return the message `DELETE 86`. This means the 86 rows where the `st` column held either `PR` or `VI` have been removed from the table.

Deleting a Column from a Table

While working on the `zip` column in the `meat_poultry_egg_inspect` table earlier in this chapter, we created a backup column called `zip_copy`. Now that we've finished working on fixing the issues in `zip`, we no longer need `zip_copy`. We can remove the backup column, including all the data within the column, from the table by using the `DROP` keyword in the `ALTER TABLE` statement.

The syntax for removing a column is similar to other `ALTER TABLE` statements:

```
ALTER TABLE table_name DROP COLUMN column_name;
```

The code in Listing 9-22 removes the `zip_copy` column:

```
ALTER TABLE meat_poultry_egg_inspect DROP COLUMN zip_copy;
```

Listing 9-22: Remove a column from a table using `DROP`

PostgreSQL returns the message `ALTER TABLE`, and the `zip_copy` column should be deleted.

Deleting a Table from a Database

The `DROP TABLE` statement is a standard ANSI SQL feature that deletes a table from the database. This statement might come in handy if, for example, you have a collection of backups, or *working tables*, that have outlived their usefulness. It's also useful in other situations, such as when you need to change the structure of a table significantly: in that case, rather than using too many `ALTER TABLE` statements, you can just remove the table and create another one by running a new `CREATE TABLE` statement.

The syntax for the `DROP TABLE` command is simple:

```
DROP TABLE table_name;
```

For example, Listing 9-23 deletes the backup version of the `meat_poultry_egg_inspect` table:

```
DROP TABLE meat_poultry_egg_inspect_backup;
```

Listing 9-23: Remove a table from a database using `DROP`

Run the query; PostgreSQL should respond with the message `DROP TABLE` to indicate the table has been removed.

Using Transaction Blocks to Save or Revert Changes

The alterations you made on data using the techniques in this chapter so far are final. That is, after you run a `DELETE` or `UPDATE` query (or any other query that alters your data or database structure), the only way to undo the change is to restore from a backup. However, you can check your changes before finalizing them and cancel the change if it's not what you intended. You do this by wrapping the SQL statement to create a *transaction block*, which is a group of statements you define using the following keywords at the beginning and end of the query:

`START TRANSACTION` signals the start of the transaction block. In PostgreSQL, you can also use the non-ANSI SQL `BEGIN` keyword.

`COMMIT` signals the end of the block and saves all changes.

`ROLLBACK` signals the end of the block and reverts all changes.

Usually, database programmers employ a transaction block to define the start and end of a sequence of operations that perform one unit of work in a database. An example is when you purchase tickets to a Broadway show. A successful transaction might involve two steps: charging your credit card and reserving your seats so someone else can't buy them. A database programmer would either want both steps in the transaction to happen (say, when your card charge goes through) or neither of them to happen (if your card is declined or you cancel at checkout). Defining both steps as one transaction keeps them as a unit; if one step fails, the other is canceled too. You can learn more details about transactions and PostgreSQL at *https://www.postgresql.org/docs/current/static/tutorial-transactions.html/*.

We can apply this transaction block technique to review changes a query makes and then decide whether to keep or discard them. Using the `meat_poultry_egg_inspect` table, let's say we're cleaning dirty data related to the company AGRO Merchants Oakland LLC. The table has three rows listing the company, but one row has an extra comma in the name:

```
company
---------------------------
AGRO Merchants Oakland LLC
AGRO Merchants Oakland LLC
AGRO Merchants Oakland, LLC
```

We want the name to be consistent, so we'll remove the comma from the third row using an UPDATE query, as we did earlier. But this time we'll check the result of our update before we make it final (and we'll purposely make a mistake we want to discard). Listing 9-24 shows how to do this using a transaction block:

```
❶ START TRANSACTION;

  UPDATE meat_poultry_egg_inspect
❷ SET company = 'AGRO Merchantss Oakland LLC'
  WHERE company = 'AGRO Merchants Oakland, LLC';

❸ SELECT company
  FROM meat_poultry_egg_inspect
  WHERE company LIKE 'AGRO%'
  ORDER BY company;

❹ ROLLBACK;
```

Listing 9-24: Demonstrating a transaction block

We'll run each statement separately, beginning with START TRANSACTION; ❶. The database responds with the message START TRANSACTION, letting you know that any succeeding changes you make to data will not be made permanent unless you issue a COMMIT command. Next, we run the UPDATE statement, which changes the company name in the row where it has an extra comma. I intentionally added an extra s in the name used in the SET clause ❷ to introduce a mistake.

When we view the names of companies starting with the letters AGRO using the SELECT statement ❸, we see that, oops, one company name is misspelled now:

```
company
---------------------------
AGRO Merchants Oakland LLC
AGRO Merchants Oakland LLC
AGRO Merchantss Oakland LLC
```

Instead of rerunning the UPDATE statement to fix the typo, we can simply discard the change by running the ROLLBACK; ❹ command. When we rerun the SELECT statement to view the company names, we're back to where we started:

```
company
---------------------------
AGRO Merchants Oakland LLC
AGRO Merchants Oakland LLC
AGRO Merchants Oakland, LLC
```

From here, you could correct your `UPDATE` statement by removing the extra `s` and rerun it, beginning with the `START TRANSACTION` statement again. If you're happy with the changes, run `COMMIT;` to make them permanent.

NOTE *When you start a transaction, any changes you make to the data aren't visible to other database users until you execute* `COMMIT`.

Transaction blocks are often used in more complex database systems. Here you've used them to try a query and either accept or reject the changes, saving you time and headaches. Next, let's look at another way to save time when updating lots of data.

Improving Performance When Updating Large Tables

Because of how PostgreSQL works internally, adding a column to a table and filling it with values can quickly inflate the table's size. (The reason is that the database creates a new version of the existing row each time a value is updated, but it doesn't delete the old row version. You'll learn how to clean up these old rows in Chapter 17 when I discuss database maintenance.) For small datasets, the increase is negligible, but for tables with hundreds of thousands or millions of rows, the time required to update rows and the resulting extra disk usage can be substantial.

Instead of adding a column and filling it with values, we can save disk space by copying the entire table and adding a populated column during the operation. Then, we rename the tables so the copy replaces the original, and the original becomes a backup.

Listing 9-25 shows how to copy `meat_poultry_egg_inspect` into a new table while adding a populated column. (To do this, we drop the `meat_poultry_egg_inspect` and `meat_poultry_egg_inspect_backup` tables we made earlier. Then we re-create `meat_poultry_egg_inspect` and reimport the data.)

```
  CREATE TABLE meat_poultry_egg_inspect_backup AS
❶ SELECT *,
❷        '2018-02-07'::date AS reviewed_date
  FROM meat_poultry_egg_inspect;
```

Listing 9-25: Backing up a table while adding and filling a new column

The query is a modified version of the backup script in Listing 9-8. Here, in addition to selecting all the columns using the asterisk wildcard ❶, we also add a column called `reviewed_date` by providing a value cast as a `date` data type ❷ and the `AS` keyword. That syntax adds and fills `reviewed_date`, which we might use to track the last time we checked the status of each plant.

Then we use Listing 9-26 to swap the table names:

```
❶ ALTER TABLE meat_poultry_egg_inspect RENAME TO meat_poultry_egg_inspect_temp;
❷ ALTER TABLE meat_poultry_egg_inspect_backup RENAME TO meat_poultry_egg_
inspect;
```

```
❸ ALTER TABLE meat_poultry_egg_inspect_temp
   RENAME TO meat_poultry_egg_inspect_backup;
```

Listing 9-26: Swapping table names using `ALTER TABLE`

Here we use `ALTER TABLE` with a `RENAME TO` clause to change a table name. Then we use the first statement to change the original table name to one that ends with `_temp` ❶. The second statement renames the copy we made with Listing 9-24 to the original name of the table ❷. Finally, we rename the table that ends with `_temp` to the ending `_backup` ❸. The original table is now called `meat_poultry_egg_inspect_backup`, and the copy with the added column is called `meat_poultry_egg_inspect`.

By using this process, we avoid updating rows and having the database inflate the size of the table. When we eventually drop the `_backup` table, the remaining data table is smaller and does not require cleanup.

Wrapping Up

Gleaning useful information from data sometimes requires modifying the data to remove inconsistencies, fix errors, and make it more suitable for supporting an accurate analysis. In this chapter you learned some useful tools to help you assess dirty data and clean it up. In a perfect world, all datasets would arrive with everything clean and complete. But given that such a perfect world doesn't exist, the ability to alter, update, and delete data will be indispensable.

Let me restate the important tasks of working safely. Be sure to back up your tables before you start making changes. Make copies of your columns, too, for an extra level of protection. When I discuss database maintenance for PostgreSQL later in the book, you'll learn how to back up entire databases. These few steps of precaution will save you a world of pain.

In the next chapter, we'll return to math to explore some of SQL's advanced statistical functions and techniques for analysis.

Try It Yourself

In this exercise, you'll turn the `meat_poultry_egg_inspect` table into useful information. You need to answer two questions: How many of the companies in the table process meat, and how many process poultry?

The answers to these two questions lie in the `activities` column. Unfortunately, the column contains an assortment of text input completely inconsistently. Here's an example of the kind of text you'll find in the `activities` column:

```
Poultry Processing, Poultry Slaughter
Meat Processing, Poultry Processing
Poultry Processing, Poultry Slaughter
```

The mishmash of text makes it impossible to perform a typical count that would allow you to group processing plants by activity. However, you can make some modifications to fix this data. Your tasks are as follows:

1. Create two new columns called `meat_processing` and `poultry_processing` in your table. Each can be of the type `boolean`.
2. Using `UPDATE`, set `meat_processing = TRUE` on any row where the `activities` column contains the text `'Meat Processing'`. Do the same update on the `poultry_processing` column, but this time look for the text `'Poultry Processing'` in `activities`.
3. Use the data from the new, updated columns to count how many companies perform each type of activity. For a bonus challenge, count how many companies perform both activities.

10

STATISTICAL FUNCTIONS IN SQL

A SQL database isn't usually the first tool a data analyst chooses when performing statistical analysis that requires more than just calculating sums and averages. Typically, the software of choice would be full-featured statistics packages, such as SPSS or SAS, the programming languages R or Python, or even Excel. However, standard ANSI SQL, including PostgreSQL's implementation, offers a handful of powerful stats functions that reveal a lot about your data without having to export your dataset to another program.

In this chapter, we'll explore these SQL stats functions along with guidelines on when to use them. Statistics is a vast subject worthy of its own book, so we'll only skim the surface here. Nevertheless, you'll learn how to apply high-level statistical concepts to help you derive meaning from your data using a new dataset from the US Census Bureau. You'll also learn to use SQL to create comparisons using rankings and rates with FBI crime data as our subject.

Creating a Census Stats Table

Let's return to one of my favorite data sources, the US Census Bureau. In Chapters 4 and 5, you used the 2010 Decennial Census to import data and perform basic math and stats. This time you'll use county data points compiled from the 2011–2015 American Community Survey (ACS) 5-Year Estimates, a separate survey administered by the Census Bureau.

Use the code in Listing 10-1 to create the table `acs_2011_2015_stats` and import the CSV file *acs_2011_2015_stats.csv*. The code and data are available with all the book's resources at *https://www.nostarch.com/SQL/*. Remember to change *`C:\YourDirectory`* to the location of the CSV file.

```
CREATE TABLE acs_2011_2015_stats (
❶    geoid varchar(14) CONSTRAINT geoid_key PRIMARY KEY,
     county varchar(50) NOT NULL,
     st varchar(20) NOT NULL,
❷    pct_travel_60_min numeric(5,3) NOT NULL,
     pct_bachelors_higher numeric(5,3) NOT NULL,
     pct_masters_higher numeric(5,3) NOT NULL,
     median_hh_income integer,
❸    CHECK (pct_masters_higher <= pct_bachelors_higher)
);

COPY acs_2011_2015_stats
FROM 'C:\YourDirectory\acs_2011_2015_stats.csv'
WITH (FORMAT CSV, HEADER, DELIMITER ',');

❹ SELECT * FROM acs_2011_2015_stats;
```

Listing 10-1: Create Census 2011–2015 ACS 5-Year stats table and import data

The `acs_2011_2015_stats` table has seven columns. The first three columns ❶ include a unique `geoid` that serves as the primary key, the name of the `county`, and the state name `st`. The next four columns display the following three percentages ❷ I derived for each county from raw data in the ACS release, plus one more economic indicator:

`pct_travel_60_min` The percentage of workers ages 16 and older who commute more than 60 minutes to work.

`pct_bachelors_higher` The percentage of people ages 25 and older whose level of education is a bachelor's degree or higher. (In the United States, a bachelor's degree is usually awarded upon completing a four-year college education.)

`pct_masters_higher` The percentage of people ages 25 and older whose level of education is a master's degree or higher. (In the United States, a master's degree is the first advanced degree earned after completing a bachelor's degree.)

`median_hh_income` The county's median household income. As you learned in Chapter 5, a median value is the midpoint in an ordered set of numbers, where half the values are larger than the midpoint and half are smaller. Because averages can be skewed by a few very large or very small values, government reporting on economic data, such as income, tends to use medians. In this column, we omit the `NOT NULL` constraint because one county had no data reported.

We include the `CHECK` constraint ❸ you learned in Chapter 7 to check that the figures for the bachelor's degree are equal to or higher than those for the master's degree, because in the United States, a bachelor's degree is earned before or concurrently with a master's degree. A county showing the opposite could indicate data imported incorrectly or a column mislabeled. Our data checks out: upon import, there are no errors showing a violation of the `CHECK` constraint.

We use the `SELECT` statement ❹ to view all 3,142 rows imported, each corresponding to a county surveyed in this Census release.

Next, we'll use statistics functions in SQL to better understand the relationships among the percentages.

THE DECENNIAL US CENSUS VS. AMERICAN COMMUNITY SURVEY

Each US Census data product has its own methodology. The Decennial Census is a full count of the US population, conducted every 10 years via a form mailed to every household in the country. One of its primary purposes is to determine the number of seats each state holds in the US House of Representatives. In contrast, the ACS is an ongoing annual survey of about 3.5 million US households. It enquires into details about income, education, employment, ancestry, and housing. Private-sector and public-sector organizations alike use ACS data to track trends and make various decisions.

Currently, the Census Bureau packages ACS data into two releases: a 1-year dataset that provides estimates for geographies with populations of 20,000 or more, and a 5-year dataset that includes all geographies. Because it's a survey, ACS results are *estimates* and have a *margin of error*, which I've omitted for brevity but you'll see included in a full ACS dataset.

Measuring Correlation with corr(Y, X)

Researchers often want to understand the relationships between variables, and one such measure of relationships is *correlation*. In this section, we'll use the `corr(Y, X)` function to measure correlation and investigate what relationship exists, if any, between the percentage of people in a county who've attained a bachelor's degree and the median household income in that county. We'll also determine whether, according to our data, a better-educated population typically equates to higher income and how strong the relationship between education level and income is if it does.

First, some background. The *Pearson correlation coefficient* (often denoted as *r* or *R*) is a measure for quantifying the strength of a *linear relationship* between two variables. It shows the extent to which an increase or decrease in one variable correlates to a change in another variable. The *r* values fall between `-1` and `1`. Either end of the range indicates a perfect correlation, whereas values near zero indicate a random distribution with no correlation. A positive *r* value indicates a *direct relationship*: as one variable increases, the other does too. When graphed on a scatterplot, the data points representing each pair of values in a direct relationship would slope upward from left to right. A negative *r* value indicates an *inverse relationship*: as one variable increases, the other decreases. Dots representing an inverse relationship would slope downward from left to right on a scatterplot.

Table 10-1 provides general guidelines for interpreting positive and negative *r* values, although as always with statistics, different statisticians may offer different interpretations.

Table 10-1: Interpreting Correlation Coefficients

Correlation coefficient (+/–)	What it could mean
0	No relationship
.01 to .29	Weak relationship
.3 to .59	Moderate relationship
.6 to .99	Strong to very strong relationship
1	Perfect relationship

In standard ANSI SQL and PostgreSQL, we calculate the Pearson correlation coefficient using `corr(Y, X)`. It's one of several *binary aggregate functions* in SQL and is so named because these functions accept two inputs. In binary aggregate functions, the input `Y` is the *dependent variable* whose variation depends on the value of another variable, and `X` is the *independent variable* whose value doesn't depend on another variable.

NOTE *Even though SQL specifies the* Y *and* X *inputs for the* `corr()` *function, correlation calculations don't distinguish between dependent and independent variables. Switching the order of inputs in* `corr()` *produces the same result. However, for convenience and readability, these examples order the input variables according to dependent and independent.*

We'll use the `corr(Y, X)` function to uncover the relationship between education level and income. Enter the code in Listing 10-2 to use `corr(Y, X)` with the `median_hh_income` and `pct_bachelors_higher` variables as inputs:

```
SELECT corr(median_hh_income, pct_bachelors_higher)
    AS bachelors_income_r
FROM acs_2011_2015_stats;
```

Listing 10-2: Using `corr(Y, X)` to measure the relationship between education and income

Run the query; your result should be an *r* value of just above `.68` given as the floating-point `double precision` data type:

```
bachelors_income_r
------------------
0.682185675451399
```

This positive *r* value indicates that as a county's educational attainment increases, household income tends to increase. The relationship isn't perfect, but the *r* value shows the relationship is fairly strong. We can visualize this pattern by plotting the variables on a scatterplot using Excel, as shown in Figure 10-1. Each data point represents one US county: the data point's position on the x-axis shows the percentage of the population ages 25 and older that have a bachelor's degree or higher. The data point's position on the y-axis represents the county's median household income.

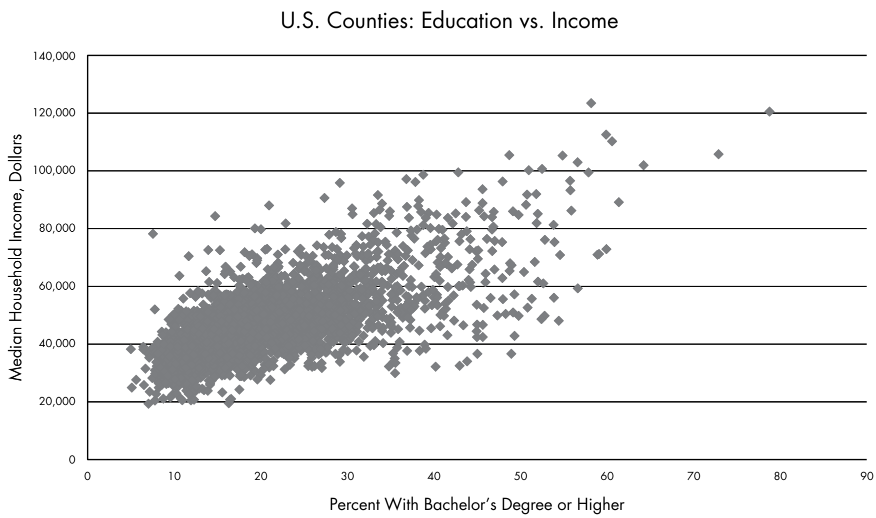


Figure 10-1: Scatterplot showing the relationship between education and income

Notice that although most of the data points are grouped together in the bottom-left corner of the graph, they do generally slope upward from left to right. Also, the points spread out rather than strictly follow a straight line. If they were in a straight line sloping up from left to right, the *r* value would be 1, indicating a perfect positive linear relationship.

Checking Additional Correlations

Now let's calculate the correlation coefficients for the remaining variable pairs using the code in Listing 10-3:

```
SELECT
❶    round(
       corr(median_hh_income, pct_bachelors_higher)::numeric, 2
```

```
    ) AS bachelors_income_r,
  round(
    corr(pct_travel_60_min, median_hh_income)::numeric, 2
    ) AS income_travel_r,
  round(
    corr(pct_travel_60_min, pct_bachelors_higher)::numeric, 2
    ) AS bachelors_travel_r
FROM acs_2011_2015_stats;
```

Listing 10-3: Using `corr(Y, X)` on additional variables

This time we'll make the output more readable by rounding off the decimal values. We'll do this by wrapping the `corr(Y, X)` function inside SQL's `round()` function ❶, which takes two inputs: the `numeric` value to be rounded and an `integer` value indicating the number of decimal places to round the first value. If the second parameter is omitted, the value is rounded to the nearest whole integer. Because `corr(Y, X)` returns a floating-point value by default, we'll change it to the `numeric` type using the `::` notation you learned in Chapter 3. Here's the output:

```
bachelors_income_r    income_travel_r    bachelors_travel_r
------------------    ---------------    ------------------
              0.68               0.05                 -0.14
```

The `bachelors_income_r` value is `0.68`, which is the same as our first run but rounded to two decimal places. Compared to `bachelors_income_r`, the other two correlations are weak.

The `income_travel_r` value shows that the correlation between income and the percentage of those who commute more than an hour to work is practically zero. This indicates that a county's median household income bears little connection to how long it takes people to get to work.

The `bachelors_travel_r` value shows that the correlation of bachelor's degrees and commuting is also low at `-0.14`. The negative value indicates an inverse relationship: as education increases, the percentage of the population who travel more than an hour to work decreases. Although this is interesting, a correlation coefficient that is this close to zero indicates a weak relationship.

When testing for correlation, we need to note some caveats. The first is that even a strong correlation does not imply causality. We can't say that a change in one variable causes a change in the other, only that the changes move together. The second is that correlations should be subject to testing to determine whether they're statistically significant. Those tests are beyond the scope of this book but worth studying on your own.

Nevertheless, the SQL `corr(Y, X)` function is a handy tool for checking correlations between variables.

Predicting Values with Regression Analysis

Researchers not only want to understand relationships between variables, they also want to predict values using available data. For example, let's say

30 percent of a county's population has a bachelor's degree or higher. Given the trend in our data, what would we expect that county's median household income to be? Likewise, for each percent increase in education, how much increase, on average, would we expect in income?

We can answer both questions using *linear regression*. Simply put, the regression method finds the best linear equation, or straight line, that describes the relationship between an independent variable (such as education) and a dependent variable (such as income). Standard ANSI SQL and PostgreSQL include functions that perform linear regression.

Figure 10-2 shows our previous scatterplot with a regression line added.

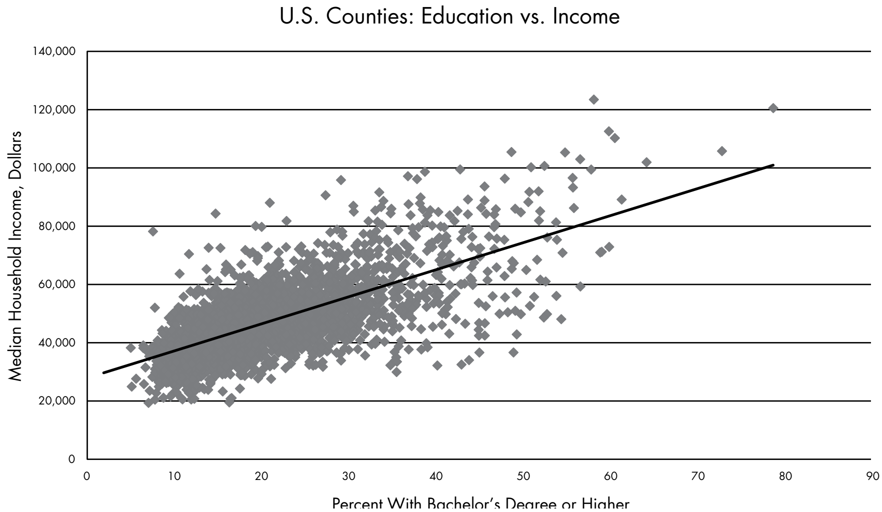


Figure 10-2: Scatterplot with least squares regression line showing the relationship between education and income

The straight line running through the middle of all the data points is called the *least squares regression line*, which approximates the "best fit" for a straight line that best describes the relationship between the variables. The equation for the regression line is the *slope-intercept* formula you might remember from high school math: $Y = bX + A$. Here are the formula's components:

***Y* is the predicted score. It's also the value on the y-axis, or dependent variable.**

***b* is the slope of the line, which can be positive or negative. It measures how many units the y-axis value will increase or decrease for each unit of the x-axis value.**

***X* represents a value on the x-axis, or independent variable.**

***A* is the y-intercept, the value at which the line crosses the y-axis when the X value is zero.**

Let's apply this formula using SQL. Earlier, we questioned what the expected median household income in a county would be if the percentage of people with a bachelor's degree or higher in that county was 30 percent. In our scatterplot, the percentage with bachelor's degrees falls along the x-axis, represented by *X* in the calculation. Let's plug that value into the slope-intercept formula in place of *X*:

$$Y = b(30) + A$$

To calculate Y, which represents the predicted median household income, we need the line's slope, *b*, and the y-intercept, *A*. To get these values, we'll use the SQL functions `regr_slope(Y, X)` and `regr_intercept(Y, X)`, as shown in Listing 10-4:

```
SELECT
    round(
        regr_slope(median_hh_income, pct_bachelors_higher)::numeric, 2
        ) AS slope,
    round(
        regr_intercept(median_hh_income, pct_bachelors_higher)::numeric, 2
        ) AS y_intercept
FROM acs_2011_2015_stats;
```

Listing 10-4: Regression slope and intercept functions

Using the `median_hh_income` and `pct_bachelors_higher` variables as inputs for both functions, we'll set the resulting value of the `regr_slope(Y, X)` function as `slope` and the output for the `regr_intercept(Y, X)` function as `y_intercept`.

Run the query; the result should show the following:

```
slope     y_intercept
------    -----------
926.95       27901.15
```

The `slope` value shows that for every one unit increase in bachelor's degree percentage, we can expect a county's median household income will increase by `926.95`. Slope always refers to change per one unit of *X*. The `y_intercept` value shows that when the regression line crosses the y-axis, where the percentage with bachelor's degrees is at 0, the y-axis value is `27901.15`. Now let's plug both values into the equation to get the Y value:

$$Y = 926.95(30) + 27901.15$$

$$Y = 55709.65$$

Based on our calculation, in a county in which 30 percent of people age 25 and older have a bachelor's degree or higher, we can expect a median household income in that county to be about $55,710. Of course, our data includes counties whose median income falls above and below that predicted value, but we expect this to be the case because our data points in the scatterplot don't line up perfectly along the regression line. Recall that the correlation coefficient we calculated was `0.68`, indicating a strong but not perfect relationship between education and income. Other factors probably contributed to variations in income as well.

Finding the Effect of an Independent Variable with r-squared

Earlier in the chapter, we calculated the correlation coefficient, *r*, to determine the direction and strength of the relationship between two variables. We can also calculate the extent that the variation in the *x* (independent) variable explains the variation in the *y* (dependent) variable by squaring the *r* value to find the *coefficient of determination*, better known as *r-squared*. r-squared is a value between zero and one that indicates the percentage of the variation that is explained by the independent variable. For example, if r-squared equals `.1`, we would say that the independent variable explains 10 percent of the variation in the dependent variable, or not much at all.

To find r-squared, we use the `regr_r2(Y, X)` function in SQL. Let's apply it to our education and income variables using the code in Listing 10-5:

```
SELECT round(
        regr_r2(median_hh_income, pct_bachelors_higher)::numeric, 3
        ) AS r_squared
FROM acs_2011_2015_stats;
```

Listing 10-5: Calculating the coefficient of determination, or r-squared

This time we'll round off the output to the nearest thousandth place and set the result to `r_squared`. The query should return the following result:

```
r_squared
---------
    0.465
```

The r-squared value of `0.465` indicates that about 47 percent of the variation in median household income in a county can be explained by the percentage of people with a bachelor's degree or higher in that county. What explains the other 53 percent of the variation in household income? Any number of factors could explain the rest of the variation, and statisticians will typically test numerous combinations of variables to determine what they are.

But before you use these numbers in a headline or presentation, it's worth revisiting the following points:

1. Correlation doesn't prove causality. For verification, do a Google search on "correlation and causality": many variables correlate well but have no meaning. (See *http://www.tylervigen.com/spurious-correlations* for examples of correlations that don't prove causality, including the correlation between divorce rate in Maine and margarine consumption.) Statisticians usually perform *significance testing* on the results to make sure values are not simply the result of randomness.
2. Statisticians also apply additional tests to data before accepting the results of a regression analysis, including whether the variables follow the standard bell curve distribution and meet other criteria for a valid result.

Given these factors, SQL's statistics functions are useful as a preliminary survey of your data before doing more rigorous analysis. If your work involves statistics, a full study on performing regression is worthwhile.

Creating Rankings with SQL

Rankings make the news often. You'll see them used anywhere from weekend box office charts to a sports team's league standings. You've already learned how to order query results based on values in a column, but SQL lets you go further and create numbered rankings. Rankings are useful for data analysis in several ways, such as when tracking changes in rankings over time if you have several years' worth of data. You can also simply use rankings as a fact on its own in a report. Let's explore how to create rankings using SQL.

Ranking with rank() and dense_rank()

Standard ANSI SQL includes several ranking functions, but we'll just focus on two: `rank()` and `dense_rank()`. Both are *window functions*, which perform calculations across sets of rows we specify using the `OVER` clause. Unlike aggregate functions, which group rows while calculating results, window functions present results for each row in the table.

The difference between `rank()` and `dense_rank()` is the way they handle the next rank value after a tie: `rank()` includes a gap in the rank order, but `dense_rank()` does not. This concept is easier to understand in action, so let's look at an example. Consider a Wall Street analyst who covers the highly competitive widget manufacturing market. The analyst wants to rank companies by their annual output. The SQL in Listing 10-6 creates and fills a table with this data and then ranks the companies by widget output:

```
CREATE TABLE widget_companies (
    id bigserial,
    company varchar(30) NOT NULL,
    widget_output integer NOT NULL
);

INSERT INTO widget_companies (company, widget_output)
VALUES
    ('Morse Widgets', 125000),
    ('Springfield Widget Masters', 143000),
    ('Best Widgets', 196000),
    ('Acme Inc.', 133000),
    ('District Widget Inc.', 201000),
    ('Clarke Amalgamated', 620000),
    ('Stavesacre Industries', 244000),
    ('Bowers Widget Emporium', 201000);

SELECT
    company,
    widget_output,
```

```
❶     rank() OVER (ORDER BY widget_output DESC),
❷     dense_rank() OVER (ORDER BY widget_output DESC)
  FROM widget_companies;
```

Listing 10-6: The `rank()` *and* `dense_rank()` *window functions*

Notice the syntax in the `SELECT` statement that includes `rank()` ❶ and `dense_rank()` ❷. After the function names, we use the `OVER` clause and in parentheses place an expression that specifies the "window" of rows the function should operate on. In this case, we want both functions to work on all rows of the `widget_output` column, sorted in descending order. Here's the output:

```
company                      widget_output    rank    dense_rank
--------------------------   -------------    ----    ----------
Clarke Amalgamated                  620000       1             1
Stavesacre Industries               244000       2             2
Bowers Widget Emporium              201000       3             3
District Widget Inc.                201000       3             3
Best Widgets                        196000       5             4
Springfield Widget Masters          143000       6             5
 Acme Inc.                          133000       7             6
 Morse Widgets                      125000       8             7
```

The columns produced by `rank()` and `dense_rank()` show each company's ranking based on the `widget_output` value from highest to lowest, with Clarke Amalgamated at number one. To see how `rank()` and `dense_rank()` differ, check the fifth row listing, Best Widgets.

With `rank()`, Best Widgets is the fifth highest ranking company, showing there are four companies with more output and there is no company ranking in fourth place, because `rank()` allows a gap in the order when a tie occurs. In contrast, `dense_rank()`, which doesn't allow a gap in the rank order, reflects the fact that Best Widgets has the fourth highest output number regardless of how many companies produced more. Therefore, Best Widgets ranks in fourth place using `dense_rank()`.

Both ways of handling ties have merit, but in practice `rank()` is used most often. It's also what I recommend using, because it more accurately reflects the total number of companies ranked, shown by the fact that Best Widgets has four companies ahead of it in total output, not three.

Let's look at a more complex ranking example.

Ranking Within Subgroups with PARTITION BY

The ranking we just did was a simple overall ranking based on widget output. But sometimes you'll want to produce ranks within groups of rows in a table. For example, you might want to rank government employees by salary within each department or rank movies by box office earnings within each genre.

To use window functions in this way, we'll add `PARTITION BY` to the `OVER` clause. `PARTITION BY` divides table rows according to values in a column we specify.

Here's an example using made-up data about grocery stores. Enter the code in Listing 10-7 to fill a table called store_sales:

```
CREATE TABLE store_sales (
    store varchar(30),
    category varchar(30) NOT NULL,
    unit_sales bigint NOT NULL,
    CONSTRAINT store_category_key PRIMARY KEY (store, category)
);

INSERT INTO store_sales (store, category, unit_sales)
VALUES
    ('Broders', 'Cereal', 1104),
    ('Wallace', 'Ice Cream', 1863),
    ('Broders', 'Ice Cream', 2517),
    ('Cramers', 'Ice Cream', 2112),
    ('Broders', 'Beer', 641),
    ('Cramers', 'Cereal', 1003),
    ('Cramers', 'Beer', 640),
    ('Wallace', 'Cereal', 980),
    ('Wallace', 'Beer', 988);

SELECT
    category,
    store,
    unit_sales,
❶   rank() OVER (PARTITION BY category ORDER BY unit_sales DESC)
FROM store_sales;
```

Listing 10-7: Apply `rank()` *within groups using* `PARTITION BY`

In the table, each row includes a store's product category and sales for that category. The final SELECT statement creates a result set showing how each store's sales ranks within each category. The new element is the addition of PARTITION BY in the OVER clause ❶. In effect, the clause tells the program to create rankings one category at a time, using the store's unit sales in descending order. Here's the output:

```
category    store      unit_sales    rank
--------    -------    ----------    ----
Beer        Wallace           988       1
Beer        Broders           641       2
Beer        Cramers           640       3
Cereal      Broders          1104       1
Cereal      Cramers          1003       2
Cereal      Wallace           980       3
Ice Cream   Broders          2517       1
Ice Cream   Cramers          2112       2
Ice Cream   Wallace          1863       3
```

Notice that category names are ordered and grouped in the `category` column as a result of `PARTITION BY` in the `OVER` clause. Rows for each category are ordered by category unit sales with the `rank` column displaying the ranking.

Using this table, we can see at a glance how each store ranks in a food category. For instance, Broders tops sales for cereal and ice cream, but Wallace wins in the beer category. You can apply this concept to many other scenarios: for example, for each auto manufacturer, finding the vehicle with the most consumer complaints; figuring out which month had the most rainfall in each of the last 20 years; or finding the team with the most wins against left-handed pitchers; and so on.

SQL offers additional window functions. Check the official PostgreSQL documentation at *https://www.postgresql.org/docs/current/static/tutorial-window.html* for an overview of window functions, and check *https://www.postgresql.org/docs/current/static/functions-window.html* for a listing of window functions.

Calculating Rates for Meaningful Comparisons

As helpful and interesting as they are, rankings based on raw counts aren't always meaningful; in fact, they can actually be misleading. Consider this example of crime statistics: according to the US Federal Bureau of Investigation (FBI), in 2015, New York City reported about 130,000 property crimes, which included burglary, larceny, motor vehicle thefts, and arson. Meanwhile, Chicago reported about 80,000 property crimes the same year.

So, you're more likely to find trouble in New York City, right? Not necessarily. In 2015, New York City had more than 8 million residents, whereas Chicago had 2.7 million. Given that context, just comparing the total numbers of property crimes in the two cities makes little sense.

A more accurate way to compare these numbers is to turn them into rates. Analysts often calculate a rate per 1,000 people, or some multiple of that number, for apples-to-apples comparisons. For the property crimes in this example, the math is simple: divide the number of offenses by the population and then multiply that quotient by 1,000. For example, if a city has 80 vehicle thefts and a population of 15,000, you can calculate the rate of vehicle thefts per 1,000 people as follows:

```
(80 / 15,000) * 1,000 = 5.3 vehicle thefts per thousand residents
```

This is easy math with SQL, so let's try it using select city-level data I compiled from the FBI's *2015 Crime in the United States* report available at *https://ucr.fbi.gov/crime-in-the-u.s/2015/crime-in-the-u.s.-2015/home*. Listing 10-8 contains the code to create and fill a table. Remember to point the script to the location in which you've saved the CSV file, which you can download at *https://www.nostarch.com/practicalSQL/*.

```
CREATE TABLE fbi_crime_data_2015 (
    st varchar(20),
    city varchar(50),
```

```
    population integer,
    violent_crime integer,
    property_crime integer,
    burglary integer,
    larceny_theft integer,
    motor_vehicle_theft integer,
    CONSTRAINT st_city_key PRIMARY KEY (st, city)
);

COPY fbi_crime_data_2015
FROM 'C:\YourDirectory\fbi_crime_data_2015.csv'
WITH (FORMAT CSV, HEADER, DELIMITER ',');

SELECT * FROM fbi_crime_data_2015
ORDER BY population DESC;
```

Listing 10-8: Create and fill a 2015 FBI crime data table

The `fbi_crime_data_2015` table includes the state, city name, and population for that city. Next is the number of crimes reported by police in categories, including violent crime, vehicle thefts, and property crime. To calculate property crimes per 1,000 people in cities with more than 500,000 people and order them, we'll use the code in Listing 10-9:

```
SELECT
    city,
    st,
    population,
    property_crime,
    round(
❶       (property_crime::numeric / population) * 1000, 1
        ) AS pc_per_1000
FROM fbi_crime_data_2015
WHERE population >= 500000
ORDER BY (property_crime::numeric / population) DESC;
```

Listing 10-9: Find property crime rates per thousand in cities with 500,000 or more people

In Chapter 5, you learned that when dividing an integer by an integer, one of the values must be a `numeric` or `decimal` for the result to include decimal places. We do that in the rate calculation ❶ with PostgreSQL's double-colon shorthand. Because we don't need to see many decimal places, we wrap the statement in the `round()` function to round off the output to the nearest tenth. Then we give the calculated column an alias of `pc_per_1000` for easy reference. Here's a portion of the result set:

```
city            st            population    property_crime    pc_per_1000
-------------   ----------    ----------    --------------    -----------
Tucson          Arizona           529675             35185           66.4
San Francisco   California        863782             53019           61.4
Albuquerque     New Mexico        559721             33993           60.7
Memphis         Tennessee         657936             37047           56.3
Seattle         Washington        683700             37754           55.2
```

```
--snip--
San Diego       California      1400467            29158           20.8
El Paso         Texas            686077            13133           19.1
```

Tucson, Arizona, has the highest rate of property crimes, followed by San Francisco, California. At the bottom is El Paso, Texas, with a rate that's one-third of Tucson's. If we had compared the cities based solely on the raw numbers of property crimes, we'd have a far different result than the one we derived by calculating the rate per thousand.

I'd be remiss not to point out that the FBI website at *https://ucr.fbi.gov/ucr-statistics-their-proper-use/* discourages creating rankings from its crime data, stating that doing so creates "misleading perceptions which adversely affect geographic entities and their residents." They point out that variations in crimes and crime rates across the country are often due to a number of factors ranging from population density to economic conditions and even the climate. Also, the FBI's crime data has well-documented shortcomings, including incomplete reporting by police agencies.

That said, asking why a locality has higher or lower crime rates than others is still worth pursuing, and rates do provide some measure of comparison despite certain limitations.

Wrapping Up

That wraps up our exploration of statistical functions in SQL, rankings, and rates. Now your SQL analysis toolkit includes ways to find relationships among variables using statistics functions, create rankings from ordered data, and properly compare raw numbers by turning them into rates. That toolkit's starting to look impressive!

Next, we'll dive deeper into date and time data, using SQL functions to extract the information we need.

Try It Yourself

Test your new skills with the following questions:

1. In Listing 10-2, the correlation coefficient, or r-value, of the variables `pct_bachelors_higher` and `median_hh_income` was about `.68`. Write a query using the same dataset to show the correlation between `pct_masters_higher` and `median_hh_income`. Is the r-value higher or lower? What might explain the difference?
2. Which cities with a population of 500,000 or more have the highest rates of motor vehicle thefts (variable `motor_vehicle_theft`)? Which have the highest violent crime rates (variable `violent_crime`)?
3. As a bonus challenge, revisit the libraries data in the table `pls_fy2014_pupld14a` in Chapter 8. Rank library agencies based on the rate of visits per 1,000 population (variable `popu_lsa`), and limit the query to agencies serving 250,000 people or more.

11

WORKING WITH DATES AND TIMES

Columns filled with dates and times can indicate *when* events happened or *how long* they took, and that can lead to interesting lines of inquiry. What patterns exist in the moments on a timeline? Which events were shortest or longest? What relationships exist between a particular activity and the time of day or season in which it occurred?

In this chapter, we'll explore these kinds of questions using SQL data types for dates and times and their related functions. We'll start with a closer look at data types and functions related to dates and times. Then we'll explore a data set that contains information on trips by New York City taxicabs to look for patterns and try to discover what, if any, story the data tells. We'll also explore time zones using Amtrak data to calculate the duration of train trips across the United States.

Data Types and Functions for Dates and Times

Chapter 3 explored primary SQL data types, but to review, here are the four data types related to dates and times:

`date` Records only the date. PostgreSQL accepts several date formats. For example, valid formats for adding the 21st day of September 2018 are `September 21, 2018` or `9/21/2018`. I recommend using `YYYY-MM-DD` (or `2018-09-21`), which is the ISO 8601 international standard format and also the default PostgreSQL date output. Using the ISO format helps avoid confusion when sharing data internationally.

`time` Records only the time. Adding `with time zone` makes the column time zone aware, as you learned in Chapter 3. The ISO 8601 format is `HH:MM:SS`, where `HH` represents the hour, `MM` the minutes, and `SS` the seconds. You can add an optional time zone designator. For example, 2:24 PM in San Francisco during standard time in fall and winter would be `14:24 PST`.

`timestamp` Records the date and time. You can add `with time zone` to make the column time zone aware. The format `timestamp with time zone` is part of the SQL standard, but with PostgreSQL, you can use the shorthand `timestamptz`, which combines the date and time formats plus a time zone designator at the end: `YYYY-MM-DD HH:MM:SS TZ`. As you learned in "Dates and Times" on page 32, you can specify time zones in three different formats: its UTC offset, an area/location designator, or a standard abbreviation.

`interval` Holds a value that represents a unit of time expressed in the format `quantity unit`. It doesn't record the start or end of a period, only its duration. Examples include `12 days` or `8 hours`.

The first three data types, `date`, `time`, and `timestamp`, are known as *datetime types* whose values are called *datetimes*. The `interval` value is an *interval type* whose values are *intervals*. All four data types can track the system clock and the nuances of the calendar. For example, `date` and `timestamp` recognize that June has 30 days. Therefore, June 31 is an invalid datetime value that causes the database to throw an error. Likewise, the date February 29 is valid only in a leap year, such as 2020.

Manipulating Dates and Times

We can use SQL functions to perform calculations on dates and times or extract components from them. For example, we can retrieve the day of the week from a timestamp or extract just the month from a date. ANSI SQL outlines a handful of functions to do this, but many database managers (including MySQL and Microsoft SQL Server) deviate from the standard to implement their own date and time data types, syntax, and function names. If you're using a database other than PostgreSQL, check its documentation.

Let's review how to manipulate dates and times using PostgreSQL functions.

Extracting the Components of a timestamp

It's not unusual to need just one piece of a date or time value for analysis, particularly when you're aggregating results by month, year, or even minute. We can extract these components using the PostgreSQL `date_part()` function. Its format looks like this:

```
date_part(text, value)
```

The function takes two inputs. The first is a string in `text` format that represents the part of the date or time to extract, such as `hour`, `minute`, or `week`. The second is the `date`, `time`, or `timestamp` value. To see the `date_part()` function in action, we'll execute it multiple times on the same value using the code in Listing 11-1. In the listing, we format the string as a `timestamp with time zone` using the PostgreSQL-specific shorthand `timestamptz`. We also assign a column name to each with `AS`.

```
SELECT
    date_part('year', '2019-12-01 18:37:12 EST'::timestamptz) AS "year",
    date_part('month', '2019-12-01 18:37:12 EST'::timestamptz) AS "month",
    date_part('day', '2019-12-01 18:37:12 EST'::timestamptz) AS "day",
    date_part('hour', '2019-12-01 18:37:12 EST'::timestamptz) AS "hour",
    date_part('minute', '2019-12-01 18:37:12 EST'::timestamptz) AS "minute",
    date_part('seconds', '2019-12-01 18:37:12 EST'::timestamptz) AS "seconds",
    date_part('timezone_hour', '2019-12-01 18:37:12 EST'::timestamptz) AS "tz",
    date_part('week', '2019-12-01 18:37:12 EST'::timestamptz) AS "week",
    date_part('quarter', '2019-12-01 18:37:12 EST'::timestamptz) AS "quarter",
    date_part('epoch', '2019-12-01 18:37:12 EST'::timestamptz) AS "epoch";
```

Listing 11-1: Extracting components of a timestamp using date_part()

Each column statement in this `SELECT` query first uses a string to name the component we want to extract: `year`, `month`, `day`, and so on. The second input uses the string `2019-12-01 18:37:12 EST` cast as a `timestamp with time zone` with the PostgreSQL double-colon syntax and the `timestamptz` shorthand. In December, most of the United States is observing standard time, which is why we can designate the Eastern time zone using the Eastern Standard Time (EST) designation.

Here's the output as shown on my computer, which is located in the US Eastern time zone. (The database converts the values to reflect your time zone, so your output might be different; for example, if you're in the US Pacific time zone, the hour will show as `15`):

```
year    month    day    hour    minute    seconds    tz    week    quarter    epoch
----    -----    ---    ----    ------    -------    --    ----    -------    ----------
2019       12      1      18        37         12    -5      48          4    1575243432
```

Each column contains a single value that represents 6:37:12 PM on December 1, 2019, in the US Eastern time zone. Even though you designated the time zone using `EST` in the string, PostgreSQL reports back the *UTC offset* of that time zone. UTC refers to Coordinated Universal Time, a world time standard, as well as the value of UTC +/- 00:00, the time zone that covers the United Kingdom and Western Africa. Here, the UTC offset is `-5` (because `EST` is five hours behind UTC).

NOTE *You can derive the UTC offset from the time zone but not vice versa. Each UTC offset can refer to multiple named time zones plus standard and daylight saving time variants.*

The first seven values are easy to recognize from the original timestamp, but the last three are calculated values that deserve an explanation.

The `week` column shows that December 1, 2019, falls in the 48th week of the year. This number is determined by ISO 8601 standards, which starts each week on a Monday. That means a week at the end of a year can extend from December in one year into January of the following year.

The `quarter` column shows that our test date is part of the 4th quarter of the year. The `epoch` column shows a measurement, which is used in computer systems and programming languages, that represents the number of seconds elapsed before or after 12:00 AM January 1, 1970, at UTC 0. A positive value designates a time since that point; a negative value designates a time before it. In this example, 1,575,243,432 seconds elapsed between January 1, 1970, and the timestamp. Epoch is useful if you need to compare two timestamps mathematically on an absolute scale.

PostgreSQL also supports the SQL-standard `extract()` function, which parses datetimes in the same way as `date_part()`. I've featured `date_part()` here instead for two reasons. First, its name helpfully reminds us what it does. Second, `extract()` isn't widely supported by database managers. Most notably, it's absent in Microsoft's SQL Server. Nevertheless, if you need to use `extract()`, the syntax takes this form:

```
extract(text from value)
```

To replicate the first `date_part()` example in Listing 11-1 where we pull the year from the timestamp, we'd set up the function like this:

```
extract('year' from '2019-12-01 18:37:12 EST'::timestamptz)
```

PostgreSQL provides additional components you can extract or calculate from dates and times. For the full list of functions, see the documentation at *https://www.postgresql.org/docs/current/static/functions-datetime.html*.

Creating Datetime Values from timestamp Components

It's not unusual to come across a data set in which the year, month, and day exist in separate columns, and you might want to create a datetime value from these components. To perform calculations on a date, it's helpful to combine and format those pieces correctly into one column.

You can use the following PostgreSQL functions to make datetime objects:

`make_date(`*`year, month, day`*`)` Returns a value of type `date`

`make_time(`*`hour, minute, seconds`*`)` Returns a value of type `time without time zone`

`make_timestamptz(`*`year, month, day, hour, minute, second, time zone`*`)` Returns a `timestamp with time zone`

The variables for these three functions take `integer` types as input but with two exceptions: seconds are of the type `double precision` because it lets you supply fractions of seconds; time zones must be specified with a `text` string that names the time zone.

Listing 11-2 shows examples of the three functions in action using components of February 22, 2018, for the date, and 6:04:30.3 PM in Lisbon, Portugal for the time:

```
SELECT make_date(2018, 2, 22);
SELECT make_time(18, 4, 30.3);
SELECT make_timestamptz(2018, 2, 22, 18, 4, 30.3, 'Europe/Lisbon');
```

Listing 11-2: Three functions for making datetimes from components

When I run each query in order, the output on my computer in the US Eastern time zone is as follows. Again, yours may differ depending on your time zone:

```
2018-02-22
18:04:30.3
2018-02-22 13:04:30.3-05
```

Notice that the timestamp in the third line shows `13:04:30.3`, which is Eastern Standard Time and is five hours behind (`-05`) the time input to the function: `18:04:30.3` PM. In our discussion on time zone–enabled columns in "Dates and Times" on page 32, I noted that PostgreSQL displays times relative to the client's time zone or the time zone set in the database session. This output reflects the appropriate time because my location is five hours behind Lisbon. We'll explore working with time zones in more detail, and you'll learn to adjust its display later in "Working with Time Zones" on page 177.

Retrieving the Current Date and Time

If you need to record the current date or time as part of a query—when updating a row, for example—standard SQL provides functions for that too. The following functions record the time as of the start of the query:

`current_date` Returns the date.

`current_time` Returns the current time with time zone

`current_timestamp` Returns the current timestamp with time zone. A shorthand PostgreSQL-specific version is `now()`.

`localtime` Returns the current time without time zone.

`localtimestamp` Returns the current timestamp without time zone.

Because these functions record the time at the start of the query (or a collection of queries grouped under a *transaction*, which I'll cover in Chapter 15), they'll provide that same time throughout the execution of a query regardless of how long the query runs. So, if your query updates 100,000 rows and takes 15 seconds to run, any timestamp recorded at the start of the query will be applied to each row, and so each row will receive the same timestamp.

If, instead, you want the date and time to reflect how the clock changes during the execution of the query, you can use the PostgreSQL-specific `clock_timestamp()` function to record the current time as it elapses. That way, if you're updating 100,000 rows and inserting a timestamp each time, each row gets the time the row updated rather than the time at the start of the query. Note that `clock_timestamp()` can slow large queries and may be subject to system limitations.

Listing 11-3 shows `current_timestamp` and `clock_timestamp()` in action when inserting a row in a table:

```
CREATE TABLE current_time_example (
    time_id bigserial,
❶   current_timestamp_col timestamp with time zone,
❷   clock_timestamp_col timestamp with time zone
);

INSERT INTO current_time_example (current_timestamp_col, clock_timestamp_col)
❸   (SELECT current_timestamp,
            clock_timestamp()
     FROM generate_series(1,1000));

SELECT * FROM current_time_example;
```

Listing 11-3: Comparing `current_timestamp` and `clock_timestamp()` during row insert

The code creates a table that includes two `timestamp` columns with a time zone. The first holds the result of the `current_timestamp` function ❶, which records the time at the start of the `INSERT` statement that adds 1,000 rows to the table. To do that, we use the `generate_series()` function, which returns a set of integers starting with 1 and ending with 1,000. The second column holds the result of the `clock_timestamp()` function ❷, which records the time of insertion of each row. You call both functions as part of the `INSERT` statement ❸. Run the query, and the result from the final `SELECT` statement should show that the time in the `current_timestamp_col` is the same for all rows, whereas the time in `clock_timestamp_col` increases with each row inserted.

Working with Time Zones

Time zone data lets the dates and times in your database reflect the location around the globe where those dates and times apply and the *UTC offset*: the number of hours plus or minus from UTC. A timestamp of 1:00 PM is only useful, for example, if you know whether the value refers to local time in Asia, Eastern Europe, one of the 12 time zones of Antarctica, or anywhere else on the globe.

Of course, very often you'll receive data sets that contain no time zone data in their datetime columns. This isn't always a deal breaker in terms of whether or not you should continue to use the data. If you know that every event in the data happened in the same location, having the time zone in the timestamp is less critical, and it's relatively easy to modify all the timestamps of your data to reflect that single time zone.

Let's look at some strategies for working with time zones in your data.

Finding Your Server's Time Zone

When working with time zones in SQL, you first need know the time zone setting for your database server. If you installed PostgreSQL on your own computer, the default will be your local time zone. If you're connecting to a PostgreSQL database elsewhere, perhaps on a network or a cloud provider such as Amazon Web Services, the time zone setting may be different than your own. To help avoid confusion when you're querying the database, it's best to set a server's time zone to UTC.

To find out the default time zone of your PostgreSQL server, use the `SHOW` command with `timezone`, as shown in Listing 11-4:

```
SHOW timezone;
```

Listing 11-4: Showing your PostgreSQL server's default time zone

Entering Listing 11-4 into pgAdmin and running it on my computer returns `US/Eastern`, one of several location names that falls into the Eastern time zone, which encompasses eastern Canada and the United States, the Caribbean, and parts of Mexico.

NOTE *You can use* `SHOW ALL` *to see the settings of every parameter on your PostgreSQL server.*

You can also use the two commands in Listing 11-5 to list all time zone names, abbreviations, and their UTC offsets:

```
SELECT * FROM pg_timezone_abbrevs;
SELECT * FROM pg_timezone_names;
```

Listing 11-5: Showing time zone abbreviations and names

You can easily filter either of these `SELECT` statements with a `WHERE` clause to look up specific location names or time zones:

```
SELECT * FROM pg_timezone_names
WHERE name LIKE 'Europe%';
```

This code should return a table listing that includes the time zone name, abbreviation, UTC offset, and a `boolean` column `is_dst` that notes whether the time zone is currently observing daylight saving time:

```
name                abbrev    utc_offset    is_dst
----------------    ------    ----------    ------
Europe/Amsterdam    CEST      02:00:00      t
Europe/Andorra      CEST      02:00:00      t
Europe/Astrakhan    +04       04:00:00      f
Europe/Athens       EEST      03:00:00      t
Europe/Belfast      BST       01:00:00      t
--snip--
```

This is a faster way of looking up time zones than using Wikipedia. Now let's look at how to set the time zone to a particular value.

Setting the Time Zone

When you installed PostgreSQL, the server's default time zone was set as a parameter in *postgresql.conf*, a file that contains dozens of values read by PostgreSQL each time it starts. The location of *postgresql.conf* in your file system varies depending on your operating system and sometimes in the way you installed PostgreSQL. To make permanent changes to *postgresql.conf*, you need to edit the file and restart the server, which might be impossible if you're not the owner of the machine. Changes to configurations might also have unintended consequences for other users or applications.

I'll cover working with this file in more depth in Chapter 17. However, for now you can easily set the pgAdmin client's time zone on a per-session basis, and the change should last as long as you're connected to the server. This solution is handy when you want to specify how you view a particular table or handle timestamps in a query.

To set and change the pgAdmin client's time zone, we use the command `SET timezone TO`, as shown in Listing 11-6:

```
❶ SET timezone TO 'US/Pacific';

❷ CREATE TABLE time_zone_test (
      test_date timestamp with time zone
  );
❸ INSERT INTO time_zone_test VALUES ('2020-01-01 4:00');

❹ SELECT test_date
  FROM time_zone_test;

❺ SET timezone TO 'US/Eastern';

❻ SELECT test_date
  FROM time_zone_test;
```

```
❼ SELECT test_date AT TIME ZONE 'Asia/Seoul'
  FROM time_zone_test;
```

Listing 11-6: Setting the time zone for a client session

First, we set the time zone to `US/Pacific` ❶, which designates the Pacific time zone that covers western Canada and the United States along with Baja California in Mexico. Second, we create a one-column table ❷ with a data type of `timestamp with time zone` and insert a single row to display a test result. Notice that the value inserted, `2020-01-01 4:00`, is a timestamp with no time zone ❸. You'll encounter timestamps with no time zone quite often, particularly when you acquire data sets restricted to a specific location.

When executed, the first `SELECT` statement ❹ turns `2020-01-01 4:00` into a timestamp that now contains time zone data:

```
test_date
----------------------
2020-01-01 04:00:00-08
```

Recall from our discussion on data types in Chapter 3 that the `-08` at the end of this timestamp is the UTC offset. In this case, the `-08` shows that the Pacific time zone is eight hours behind UTC. Because we initially set the pgAdmin client's time zone to `US/Pacific` for this session, any value we now enter into a column that is time zone aware will be in Pacific time and coded accordingly. However, it's worth noting that on the server, the `timestamp with time zone` data type always stores data as UTC internally; the time zone setting governs how it's displayed.

Now comes some fun. We change the time zone for this session to the Eastern time zone using the `SET` command ❺ and the `US/Eastern` designation. Then, when we execute the `SELECT` statement ❻ again, the result should be as follows:

```
test_date
----------------------
2020-01-01 07:00:00-05
```

In this example, two components of the timestamp have changed: the time is now `07:00`, and the UTC offset is `-05` because we're viewing the timestamp from the perspective of the Eastern time zone: 4:00 AM Pacific is 7:00 AM Eastern. The original Pacific time value remains unaltered in the table, and the database converts it to show the time in whatever time zone we set at ❺.

Even more convenient is that we can view a timestamp through the lens of any time zone without changing the session setting. The final `SELECT` statement uses the `AT TIME ZONE` keywords ❼ to display the timestamp in our session as Korea standard time (KST) by specifying `Asia/Seoul`:

```
timezone
-------------------
2020-01-01 21:00:00
```

Now we know that the database value of 4:00 AM in `US/Pacific` on January 1, 2020, is equivalent to 9:00 PM that same day in `Asia/Seoul`. Again, this modification alters the output, but the data on the server remains unchanged, although this syntax does change the output data type. If the original value is a `timestamp with time zone`, the output removes the time zone. If the original value has no time zone, the output is `timestamp with time zone`.

The ability of databases to track time zones is extremely important for accurate calculations of intervals, as you'll see next.

Calculations with Dates and Times

We can perform simple arithmetic on dates and times the same way we can on numbers. Addition, subtraction, multiplication, and division are all possible in PostgreSQL using the math operators `+`, `-`, `*`, and `/`. For example, you can subtract one date from another date to get an integer that represents the difference in days between the two dates. For example, the following code returns an integer of `3`:

```
SELECT '9/30/1929'::date - '9/27/1929'::date;
```

The result indicates that these two dates are exactly three days apart.

Likewise, you can use the following code to add a time interval to a date to return a new date:

```
SELECT '9/30/1929'::date + '5 years'::interval;
```

This code adds five years to the date `9/30/1929` to return a timestamp value of `9/30/1934`.

You can find more examples of math functions you can use with dates and times in the PostgreSQL documentation at *https://www.postgresql.org/docs/current/static/functions-datetime.html*. Let's explore some more practical examples using actual transportation data.

Finding Patterns in New York City Taxi Data

Every time I visit New York City, I usually take at least one ride in one of the 13,500 iconic yellow cars that ferry hundreds of thousands of people across the city's five boroughs each day. The New York City Taxi and Limousine Commission releases data on monthly yellow taxi trips plus other for-hire vehicles. We'll use this large, rich data set to put date functions to practical use.

The *yellow_tripdata_2016_06_01.csv* file available from the book's resources (at *https://www.nostarch.com/practicalSQL/*) holds one day of yellow taxi trip records from June 1, 2016. Save the file to your computer and execute the code in Listing 11-7 to build the `nyc_yellow_taxi_trips_2016_06_01` table. Remember to change the file path in the `COPY` command to the location where you've saved the file and adjust the path format to reflect whether you're using Windows, macOS, or Linux.

```
❶ CREATE TABLE nyc_yellow_taxi_trips_2016_06_01 (
    trip_id bigserial PRIMARY KEY,
    vendor_id varchar(1) NOT NULL,
    tpep_pickup_datetime timestamp with time zone NOT NULL,
    tpep_dropoff_datetime timestamp with time zone NOT NULL,
    passenger_count integer NOT NULL,
    trip_distance numeric(8,2) NOT NULL,
    pickup_longitude numeric(18,15) NOT NULL,
    pickup_latitude numeric(18,15) NOT NULL,
    rate_code_id varchar(2) NOT NULL,
    store_and_fwd_flag varchar(1) NOT NULL,
    dropoff_longitude numeric(18,15) NOT NULL,
    dropoff_latitude numeric(18,15) NOT NULL,
    payment_type varchar(1) NOT NULL,
    fare_amount numeric(9,2) NOT NULL,
    extra numeric(9,2) NOT NULL,
    mta_tax numeric(5,2) NOT NULL,
    tip_amount numeric(9,2) NOT NULL,
    tolls_amount numeric(9,2) NOT NULL,
    improvement_surcharge numeric(9,2) NOT NULL,
    total_amount numeric(9,2) NOT NULL
);

❷ COPY nyc_yellow_taxi_trips_2016_06_01 (
    vendor_id,
    tpep_pickup_datetime,
    tpep_dropoff_datetime,
    passenger_count,
    trip_distance,
    pickup_longitude,
    pickup_latitude,
    rate_code_id,
    store_and_fwd_flag,
    dropoff_longitude,
    dropoff_latitude,
    payment_type,
    fare_amount,
    extra,
    mta_tax,
    tip_amount,
    tolls_amount,
    improvement_surcharge,
    total_amount
   )
```

```
FROM 'C:\YourDirectory\yellow_tripdata_2016_06_01.csv'
WITH (FORMAT CSV, HEADER, DELIMITER ',');

❸ CREATE INDEX tpep_pickup_idx
ON nyc_yellow_taxi_trips_2016_06_01 (tpep_pickup_datetime);
```

Listing 11-7: Creating a table and importing NYC yellow taxi data

The code in Listing 11-7 builds the table ❶, imports the rows ❷, and creates an index ❸. In the `COPY` statement, we provide the names of columns because the input CSV file doesn't include the `trip_id` column that exists in the target table. That column is of type `bigserial`, which you've learned is an auto-incrementing integer and will fill automatically. After your import is complete, you should have 368,774 rows, one for each yellow cab ride on June 6, 2016. You can check the number of rows in your table with a count using the following code:

```
SELECT count(*) FROM nyc_yellow_taxi_trips_2016_06_01;
```

Each row includes data on the number of passengers, the location of pickup and drop-off via latitude and longitude, and the fare and tips in US dollars. The data dictionary that describes all columns and codes is available at *http://www.nyc.gov/html/tlc/downloads/pdf/data_dictionary_trip_records_yellow.pdf*. For these exercises, we're most interested in the timestamp columns `tpep_pickup_datetime` and `tpep_dropoff_datetime`, which represent the start and end times of the ride. (The Technology Passenger Enhancements Project (TPEP) is a program that in part includes automated collection of data about taxi rides.)

The values in both timestamp columns include the time zone provided by the Taxi and Limousine Commission. In all rows of the CSV file, the time zone included with the timestamp is shown as `-4`, which is the summertime UTC offset for the Eastern time zone when New York City and the rest of the US East Coast observe daylight saving time. If you're not or your PostgreSQL server isn't located in Eastern time, I suggest setting your time zone using the following code so your results will match mine:

```
SET timezone TO 'US/Eastern';
```

Now let's explore the patterns we can identify in the data related to these times.

The Busiest Time of Day

One question you might ask after viewing this data set is when taxis provide the most rides. Is it morning or evening rush hour, or is there another time—at least, on this day—when rides spiked? You can determine the answer with a simple aggregation query that uses `date_part()`.

Listing 11-8 contains the SQL to count rides by hour using the pickup time as the input:

```
SELECT
❶   date_part('hour', tpep_pickup_datetime) AS trip_hour,
❷   count(*)
FROM nyc_yellow_taxi_trips_2016_06_01
GROUP BY trip_hour
ORDER BY trip_hour;
```

Listing 11-8: Counting taxi trips by hour

In the query's first column ❶, `date_part()` extracts the hour from `tpep_pickup_datetime` so we can group the number of rides by hour. Then we aggregate the number of rides in the second column via the `count()` function ❷. The rest of the query follows the standard patterns for grouping and ordering the results, which should return 24 rows, one for each hour of the day:

```
trip_hour    count
---------    -----
        0     8182
        1     5003
        2     3070
        3     2275
        4     2229
        5     3925
        6    10825
        7    18287
        8    21062
        9    18975
       10    17367
       11    17383
       12    18031
       13    17998
       14    19125
       15    18053
       16    15069
       17    18513
       18    22689
       19    23190
       20    23098
       21    24106
       22    22554
       23    17765
```

Eyeballing the numbers, it's apparent that on June 6, 2016, New York City taxis had the most passengers between 6:00 PM and 10:00 PM, possibly reflecting commutes home plus the plethora of city activities on a summer evening. But to see the overall pattern, it's best to visualize the data. Let's do this next.

Exporting to CSV for Visualization in Excel

Charting data with a tool such as Microsoft Excel makes it easier to understand patterns, so I often export query results to a CSV file and work up a quick chart. Listing 11-9 uses the query from the preceding example within a `COPY ... TO` statement, similar to Listing 4-9 on page 54:

```
COPY
    (SELECT
        date_part('hour', tpep_pickup_datetime) AS trip_hour,
        count(*)
    FROM nyc_yellow_taxi_trips_2016_06_01
    GROUP BY trip_hour
    ORDER BY trip_hour
    )
TO 'C:\YourDirectory\hourly_pickups_2016_06_01.csv'
WITH (FORMAT CSV, HEADER, DELIMITER ',');
```

Listing 11-9: Exporting taxi pickups per hour to a CSV file

When I load the data into Excel and build a line graph, the day's pattern becomes more obvious and thought-provoking, as shown in Figure 11-1.

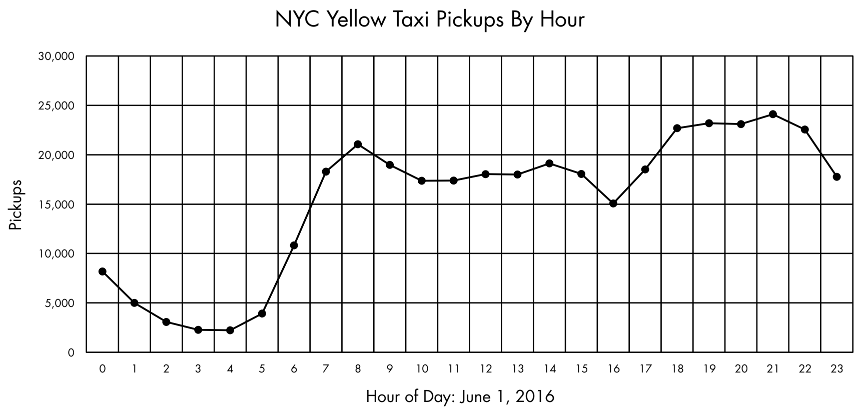


Figure 11-1: NYC yellow taxi pickups by hour

Rides bottomed out in the wee hours of the morning before rising sharply between 5:00 AM and 8:00 AM. Volume remained relatively steady throughout the day and increased again for evening rush hour after 5:00 PM. But there was a dip between 3:00 PM and 4:00 PM—why?

To answer that question, we would need to dig deeper to analyze data that spanned several days or even several months to see whether our data from June 1, 2016, is typical. We could use the `date_part()` function to compare trip volume on weekdays versus weekends by extracting the day of the week. To be even more ambitious, we could check weather reports and compare trips on rainy days versus sunny days. There are many different ways to slice a data set to derive conclusions.

When Do Trips Take the Longest?

Let's investigate another interesting question: at which hour did taxi trips take the longest? One way to find an answer is to calculate the median trip time for each hour. The median is the middle value in an ordered set of values; it's usually more accurate than mean averages for making comparisons because a few very small or very large values in the set won't skew the results as they would with the mean.

In Chapter 5, we used the `percentile_cont()` function to find medians. We use it again in Listing 11-10 to calculate median trip times:

```
SELECT
❶   date_part('hour', tpep_pickup_datetime) AS trip_hour,
❷   percentile_cont(.5)
❸       WITHIN GROUP (ORDER BY
         tpep_dropoff_datetime - tpep_pickup_datetime) AS median_trip
FROM nyc_yellow_taxi_trips_2016_06_01
GROUP BY trip_hour
ORDER BY trip_hour;
```

Listing 11-10: Calculating median trip time by hour

We're aggregating data by the hour portion of the timestamp column `tpep_pickup_datetime` again, which we extract using `date_part()` ❶. For the input to the `percentile_cont()` function ❷, we subtract the pickup time from the drop-off time in the `WITHIN GROUP` clause ❸. The results show that the 1:00 PM hour has the highest median trip time of 15 minutes:

```
date_part    median_trip
---------    -----------
        0    00:10:04
        1    00:09:27
        2    00:08:59
        3    00:09:57
        4    00:10:06
        5    00:07:37
        6    00:07:54
        7    00:10:23
        8    00:12:28
        9    00:13:11
       10    00:13:46
       11    00:14:20
       12    00:14:49
       13    00:15:00
       14    00:14:35
       15    00:14:43
       16    00:14:42
       17    00:14:15
       18    00:13:19
       19    00:12:25
       20    00:11:46
       21    00:11:54
```

```
22    00:11:37
23    00:11:14
```

As we would expect, trip times are shortest in the early morning hours. This result makes sense because less traffic in the early morning means passengers are more likely to get to their destinations faster.

Now that we've explored ways to extract portions of the timestamp for analysis, let's dig deeper into analysis that involves intervals.

Finding Patterns in Amtrak Data

Amtrak, the nationwide rail service in America, offers several packaged trips across the United States. The All American, for example, is a train that departs from Chicago and stops in New York, New Orleans, Los Angeles, San Francisco, and Denver before returning to Chicago. Using data from the Amtrak website (*http://www.amtrak.com/*), we'll build a table that shows information for each segment of the trip. The trip spans four time zones, so we'll need to track the time zones each time we enter an arrival or departure time. Then we'll calculate the duration of the journey at each segment and figure out the length of the entire trip.

Calculating the Duration of Train Trips

Let's create a table that divides The All American train route into six segments. Listing 11-11 contains SQL to create and fill a table with the departure and arrival time for each leg of the journey:

```
❶ SET timezone TO 'US/Central';

CREATE TABLE train_rides (
    trip_id bigserial PRIMARY KEY,
    segment varchar(50) NOT NULL,
❷   departure timestamp with time zone NOT NULL,
    arrival timestamp with time zone NOT NULL
);

INSERT INTO train_rides (segment, departure, arrival)
VALUES
❸   ('Chicago to New York', '2017-11-13 21:30 CST', '2017-11-14 18:23 EST'),
    ('New York to New Orleans', '2017-11-15 14:15 EST', '2017-11-16 19:32
CST'),
    ('New Orleans to Los Angeles', '2017-11-17 13:45 CST', '2017-11-18 9:00
PST'),
    ('Los Angeles to San Francisco', '2017-11-19 10:10 PST', '2017-11-19 21:24
PST'),
    ('San Francisco to Denver', '2017-11-20 9:10 PST', '2017-11-21 18:38
MST'),
    ('Denver to Chicago', '2017-11-22 19:10 MST', '2017-11-23 14:50 CST');

SELECT * FROM train_rides;
```

Listing 11-11: Creating a table to hold train trip data

To start, we set the server to the Central time zone, the value for Chicago, using the US/Central designator ❶. We'll use Central time as our reference when viewing the timestamps of the data we enter so that regardless of your and my machine's default time zones, we'll share the same view of the data.

Next, we use the standard CREATE TABLE statement. Note that columns for departures and arrival times are set to timestamp with time zone ❷. Finally, we insert rows that represent the six legs of the trip ❸. Each timestamp input reflects the time zone of the departure and arrival city. Specifying the city's time zone is the key to getting an accurate calculation of trip duration and accounting for time zone changes. It also accounts for annual changes to and from daylight saving time if they were to occur during the time span you're examining.

The final SELECT statement should return the contents of the table like this:

```
trip_id    segment                         departure                  arrival
-------    ----------------------------    ----------------------     ----------------------
      1    Chicago to New York             2017-11-13 21:30:00-06     2017-11-14 17:23:00-06
      2    New York to New Orleans         2017-11-15 13:15:00-06     2017-11-16 19:32:00-06
      3    New Orleans to Los Angeles      2017-11-17 13:45:00-06     2017-11-18 11:00:00-06
      4    Los Angeles to San Francisco    2017-11-19 12:10:00-06     2017-11-19 23:24:00-06
      5    San Francisco to Denver         2017-11-20 11:10:00-06     2017-11-21 19:38:00-06
      6    Denver to Chicago               2017-11-22 20:10:00-06     2017-11-23 14:50:00-06
```

All timestamps should now carry a UTC offset of -06, which is equivalent to the Central time zone in the United States during the month of November, when the nation is under standard time. Regardless of the time zone we supplied on insert, our view of the data is now in Central time, and the times are adjusted accordingly if they're in another time zone.

Now that we've created segments corresponding to each leg of the trip, we'll use Listing 11-12 to calculate the duration of each segment:

```
SELECT segment,
❶       to_char(departure, 'YYYY-MM-DD HH12:MI a.m. TZ') AS departure,
❷       arrival - departure AS segment_time
FROM train_rides;
```

Listing 11-12: Calculating the length of each trip segment

This query lists the trip segment, the departure time, and the duration of the segment journey. Before we look at the calculation, notice the additional code around the departure column ❶. These are PostgreSQL-specific formatting functions that specify how to format different components of the timestamp. In this case, the to_char() function turns the departure timestamp column into a string of characters formatted as YYYY-MM-DD HH12:MI a.m. TZ. The YYYY-MM-DD portion specifies the ISO format for the date, and the HH12:MI a.m. portion presents the time in hours and minutes. The HH12 portion specifies the use of a 12-hour clock rather than 24-hour military time. The `a.m.` portion specifies that we want to show morning or night times using lowercase characters separated by periods, and the `TZ` portion denotes the time zone.

For a complete list of formatting functions, check out the PostgreSQL documentation at *https://www.postgresql.org/docs/current/static/functions-formatting.html*.

Finally, we subtract `departure` from `arrival` to determine the `segment_time` ❷. When you run the query, the output should look like this:

```
segment                         departure                    segment_time
----------------------------    -------------------------    ------------
Chicago to New York             2017-11-13 09:30 p.m. CST    19:53:00
New York to New Orleans         2017-11-15 01:15 p.m. CST    1 day 06:17:00
New Orleans to Los Angeles      2017-11-17 01:45 p.m. CST    21:15:00
Los Angeles to San Francisco    2017-11-19 12:10 p.m. CST    11:14:00
San Francisco to Denver         2017-11-20 11:10 a.m. CST    1 day 08:28:00
Denver to Chicago               2017-11-22 08:10 p.m. CST    18:40:00
```

Subtracting one timestamp from another produces an `interval` data type, which was introduced in Chapter 3. As long as the value is less than 24 hours, PostgreSQL presents the interval in the `HH:MM:SS` format. For values greater than 24 hours, it returns the format `1 day 08:28:00`, as shown in the San Francisco to Denver segment.

In each calculation, PostgreSQL accounts for the changes in time zones so we don't inadvertently add or lose hours when subtracting. If we used a `timestamp without time zone` data type, we would end up with an incorrect trip length if a segment spanned multiple time zones.

Calculating Cumulative Trip Time

As it turns out, San Francisco to Denver is the longest leg of The All American train trip. But how long does the entire trip take? To answer this question, we'll revisit window functions, which you learned about in "Ranking with rank() and dense_rank()" on page 166.

Our prior query produced an interval, which we labeled `segment_time`. It would seem like the natural next step would be to write a query to add those values, creating a cumulative interval after each segment. And indeed, we can use `sum()` as a window function, combined with the `OVER` clause mentioned in Chapter 10, to create running totals. But when we do, the resulting values are odd. To see what I mean, run the code in Listing 11-13:

```
SELECT segment,
       arrival - departure AS segment_time,
       sum(arrival - departure) OVER (ORDER BY trip_id) AS cume_time
FROM train_rides;
```

Listing 11-13: Calculating cumulative intervals using `OVER`

In the third column, we sum the intervals generated when we subtract `departure` from `arrival`. The resulting running total in the `cume_time` column is accurate but formatted in an unhelpful way:

```
segment                        segment_time      cume_time
----------------------------   --------------    ---------------
Chicago to New York            19:53:00          19:53:00
New York to New Orleans        1 day 06:17:00    1 day 26:10:00
New Orleans to Los Angeles     21:15:00          1 day 47:25:00
Los Angeles to San Francisco   11:14:00          1 day 58:39:00
San Francisco to Denver        1 day 08:28:00    2 days 67:07:00
Denver to Chicago              18:40:00          2 days 85:47:00
```

PostgreSQL creates one sum for the day portion of the interval and another for the hours and minutes. So, instead of a more understandable cumulative time of `5 days 13:47:00`, the database reports `2 days 85:47:00`. Both results amount to the same length of time, but `2 days 85:47:00` is harder to decipher. This is an unfortunate limitation of summing the database intervals using this syntax.

As a workaround, we'll use the code in Listing 11-14:

```
SELECT segment,
       arrival - departure AS segment_time,
       sum(date_part❶('epoch', (arrival - departure)))
           OVER (ORDER BY trip_id) * interval '1 second'❷ AS cume_time
FROM train_rides;
```

Listing 11-14: Better formatting for cumulative trip time

Recall from earlier in this chapter that `epoch` is the number of seconds that have elapsed since midnight on January 1, 1970, which makes it useful for calculating duration. In Listing 11-14, we use `date_part()` ❶ with the `epoch` setting to extract the number of seconds elapsed between the arrival and departure intervals. Then we multiply each sum with an interval of `1 second` ❷ to convert those seconds to an `interval` value. The output is clearer using this method:

```
segment                        segment_time      cume_time
----------------------------   --------------    ---------
Chicago to New York            19:53:00          19:53:00
New York to New Orleans        1 day 06:17:00    50:10:00
New Orleans to Los Angeles     21:15:00          71:25:00
Los Angeles to San Francisco   11:14:00          82:39:00
San Francisco to Denver        1 day 08:28:00    115:07:00
Denver to Chicago              18:40:00          133:47:00
```

The final `cume_time`, now in `HH:MM:SS` format, adds all the segments to return the total trip length of 133 hours and 47 minutes. That's a long time to spend on a train, but I'm sure the scenery is well worth the ride.

Wrapping Up

Handling times and dates in SQL databases adds an intriguing dimension to your analysis, letting you answer questions about when an event occurred along with other temporal concerns in your data. With a solid grasp of time and date formats, time zones, and functions to dissect the components of a timestamp, you can analyze just about any data set you come across.

Next, we'll look at advanced query techniques that help answer more complex questions.

Try It Yourself

Try these exercises to test your skills on dates and times.

1. Using the New York City taxi data, calculate the length of each ride using the pickup and drop-off timestamps. Sort the query results from the longest ride to the shortest. Do you notice anything about the longest or shortest trips that you might want to ask city officials about?
2. Using the `AT TIME ZONE` keywords, write a query that displays the date and time for London, Johannesburg, Moscow, and Melbourne the moment January 1, 2100, arrives in New York City.
3. As a bonus challenge, use the statistics functions in Chapter 10 to calculate the correlation coefficient and r-squared values using trip time and the `total_amount` column in the New York City taxi data, which represents the total amount charged to passengers. Do the same with `trip_distance` and `total_amount`. Limit the query to rides that last three hours or less.

12

ADVANCED QUERY TECHNIQUES

Sometimes data analysis requires advanced SQL techniques that go beyond a table join or basic `SELECT` query. For example, to find the story in your data, you might need to write a query that uses the results of other queries as inputs. Or you might need to reclassify numerical values into categories before counting them. Like other programming languages, SQL provides a collection of functions and options essential for solving more complex problems, and that is what we'll explore in this chapter.

For the exercises, I'll introduce a data set of temperatures recorded in select US cities and we'll revisit data sets you've created in previous chapters. The code for the exercises is available, along with all the book's resources, at *https://www.nostarch.com/practicalSQL/*. You'll continue to use the `analysis` database you've already built. Let's get started.

Using Subqueries

A *subquery* is nested inside another query. Typically, it's used for a calculation or logical test that provides a value or set of data to be passed into the main portion of the query. Its syntax is not unusual: we just enclose the subquery in parentheses and use it where needed. For example, we can write a subquery that returns multiple rows and treat the results as a table in the FROM clause of the main query. Or we can create a *scalar subquery* that returns a single value and use it as part of an *expression* to filter rows via WHERE, IN, and HAVING clauses. These are the most common uses of subqueries.

You first encountered a subquery in Chapter 9 in the ANSI SQL standard syntax for a table UPDATE, which is shown again here. Both the data for the update and the condition that specifies which rows to update are generated by subqueries that look for values that match the columns in *table* and *table_b*:

```
UPDATE table
❶ SET column = (SELECT column
                FROM table_b
                WHERE table.column = table_b.column)
❷ WHERE EXISTS (SELECT column
                FROM table_b
                WHERE table.column = table_b.column);
```

This example query has two subqueries that use the same syntax. We use the SELECT statement inside parentheses ❶ as the first subquery in the SET clause, which generates values for the update. Similarly, we use a second subquery in the WHERE EXISTS clause, again with a SELECT statement ❷ to filter the rows we want to update. Both subqueries are *correlated subqueries* and are so named because they depend on a value or table name from the main query that surrounds them. In this case, both subqueries depend on *table* from the main UPDATE statement. An *uncorrelated subquery* has no reference to objects in the main query.

It's easier to understand these concepts by working with actual data, so let's look at some examples. We'll revisit two data sets from earlier chapters: the Decennial 2010 Census table us_counties_2010 you created in Chapter 4 and the meat_poultry_egg_inspect table in Chapter 9.

Filtering with Subqueries in a WHERE Clause

You know that a WHERE clause lets you filter query results based on criteria you provide, using an expression such as WHERE quantity > 1000. But this requires that you already know the value to use for comparison. What if you don't? That's one way a subquery comes in handy: it lets you write a query that generates one or more values to use as part of an expression in a WHERE clause.

Generating Values for a Query Expression

Say you wanted to write a query to show which US counties are at or above the 90th percentile, or top 10 percent, for population. Rather than writing two separate queries—one to calculate the 90th percentile and the other to filter by counties—you can do both at once using a subquery in a WHERE clause, as shown in Listing 12-1:

```
SELECT geo_name,
       state_us_abbreviation,
       p0010001
FROM us_counties_2010
❶ WHERE p0010001 >= (
    SELECT percentile_cont(.9) WITHIN GROUP (ORDER BY p0010001)
    FROM us_counties_2010
    )
ORDER BY p0010001 DESC;
```

Listing 12-1: Using a subquery in a WHERE clause

This query is standard in terms of what we've done so far except that the WHERE clause ❶, which filters by the total population column p0010001, doesn't include a value like it normally would. Instead, after the >= comparison operators, we provide a second query in parentheses. This second query uses the percentile_cont() function in Chapter 5 to generate one value: the 90th percentile cut-off point in the p0010001 column, which will then be used in the main query.

NOTE *Using percentile_cont() to filter with a subquery works only if you pass in a single input, as shown. If you pass in an array, as in Listing 5-12 on page 90, percentile_cont() returns an array, and the query will fail to evaluate the >= against an array type.*

If you run the subquery separately by highlighting it in pgAdmin, you should see the results of the subquery, a value of 197444.6. But you won't see that number when you run the entire query in Listing 12-1, because the result of that subquery is passed directly to the WHERE clause to use in filtering the results.

The entire query should return 315 rows, or about 10 percent of the 3,143 rows in us_counties_2010.

```
geo_name            state_us_abbreviation    p0010001
------------------  ---------------------    --------
Los Angeles County  CA                       9818605
Cook County         IL                       5194675
Harris County       TX                       4092459
Maricopa County     AZ                       3817117
San Diego County    CA                       3095313
--snip--
Elkhart County      IN                        197559
Sangamon County     IL                        197465
```

The result includes all counties with a population greater than or equal to 197444.6, the value the subquery generated.

Using a Subquery to Identify Rows to Delete

Adding a subquery to a `WHERE` clause can be useful in query statements other than `SELECT`. For example, we can use a similar subquery in a `DELETE` statement to specify what to remove from a table. Imagine you have a table with 100 million rows that, because of its size, takes a long time to query. If you just want to work on a subset of the data (such as a particular state), you can make a copy of the table and delete what you don't need from it.

Listing 12-2 shows an example of this approach. It makes a copy of the Census table using the method you learned in Chapter 9 and then deletes everything from that backup except the 315 counties in the top 10 percent of population:

```
SELECT * INTO us_counties_2010_top10
FROM us_counties_2010;

DELETE FROM us_counties_2010_top10
WHERE p0010001 < (
    SELECT percentile_cont(.9) WITHIN GROUP (ORDER BY p0010001)
    FROM us_counties_2010_top10
    );
```

Listing 12-2: Using a subquery in a `WHERE` clause with `DELETE`

Run the code in Listing 12-2, and then execute `SELECT count(*) FROM us_counties_2010_top10;` to count the remaining rows in the table. The result should be 315 rows, which is the original 3,143 minus the 2,828 the subquery deleted.

Creating Derived Tables with Subqueries

If your subquery returns rows and columns of data, you can convert that data to a table by placing it in a `FROM` clause, the result of which is known as a *derived table*. A derived table behaves just like any other table, so you can query it or join it to other tables, even other derived tables. This approach is helpful when a single query can't perform all the operations you need.

Let's look at a simple example. In Chapter 5, you learned the difference between average and median values. I explained that a median can often better indicate a data set's central value because a few very large or small values (or outliers) can skew an average. For that reason, I often recommend comparing the average and median. If they're close, the data probably falls in a *normal distribution* (the familiar bell curve), and the average is a good representation of the central value. If the average and median are far apart, some outliers might be having an effect or the distribution is skewed, not normal.

Finding the average and median population of US counties as well as the difference between them is a two-step process. We need to calculate the average and the median, and then we need to subtract the two. We can do both operations in one fell swoop with a subquery in the `FROM` clause, as shown in Listing 12-3:

```
SELECT round(calcs.average, 0) AS average,
       calcs.median,
       round(calcs.average - calcs.median, 0) AS median_average_diff
FROM (
❶    SELECT avg(p0010001) AS average,
            percentile_cont(.5)
                WITHIN GROUP (ORDER BY p0010001)::numeric(10,1) AS median
     FROM us_counties_2010
     )
❷ AS calcs;
```

Listing 12-3: Subquery as a derived table in a `FROM` *clause*

The subquery ❶ is straightforward. We use the `avg()` and `percentile_cont()` functions to find the average and median of the Census table's `p0010001` total population column and name each column with an alias. Then we name the subquery with an alias ❷ of `calcs` so we can reference it as a table in the main query.

Subtracting the `median` from the `average`, both of which are returned by the subquery, is done in the main query; then the main query rounds the result and labels it with the alias `median_average_diff`. Run the query, and the result should be the following:

```
average    median     median_average_diff
-------    -------    -------------------
  98233    25857.0                  72376
```

The difference between the median and average, 72,736, is nearly three times the size of the median. That helps show that a relatively small number of high-population counties push the average county size over 98,000, whereas the median (or middle value) of all counties is much less at 25,857.

Joining Derived Tables

Because derived tables behave like regular tables, you can join them. Joining derived tables lets you perform multiple preprocessing steps before arriving at the result. For example, say we wanted to determine which states have the most meat, egg, and poultry processing plants per million population; before we can calculate that rate, we need to know the number of plants in each state and the population of each state.

We start by counting producers by state using the `meat_poultry_egg_inspect` table in Chapter 9. Then we can use the `us_counties_2010` table to count population by state by summing and grouping county values. Listing 12-4 shows how to write subqueries for both tasks and join them to calculate the overall rate.

```
SELECT census.state_us_abbreviation AS st,
       census.st_population,
       plants.plant_count,
❶      round((plants.plant_count/census.st_population::numeric(10,1))*1000000, 1)
           AS plants_per_million
FROM
    (
❷       SELECT st,
               count(*) AS plant_count
        FROM meat_poultry_egg_inspect
        GROUP BY st
    )
    AS plants
JOIN
    (
❸       SELECT state_us_abbreviation,
               sum(p0010001) AS st_population
        FROM us_counties_2010
        GROUP BY state_us_abbreviation
    )
    AS census
❹ ON plants.st = census.state_us_abbreviation
ORDER BY plants_per_million DESC;
```

Listing 12-4: Joining two derived tables

You learned how to calculate rates in Chapter 10, so the math and syntax in the main query for finding `plants_per_million` ❶ should be familiar. We divide the number of plants by the population, and then multiply that quotient by 1 million. For the inputs, we use the values generated from derived tables using subqueries.

The first subquery ❷ finds the number of plants in each state using the `count()` aggregate function and then groups them by state. We label this subquery with the `plants` alias for reference in the main part of the query. The second subquery ❸ finds the total population by state by using `sum()` on the `p0010001` total population column and then groups those by `state_us_abbreviation`. We alias this derived table as `census`.

Next, we `JOIN` the derived tables ❹ by linking the `st` column in `plants` to the `state_us_abbreviation` column in `census`. We then list the results in descending order based on the calculated rates. Here's a sample output of 51 rows showing the highest and lowest rates:

```
st    st_population    plant_count    plants_per_million
--    -------------    -----------    ------------------
NE          1826341            111                  60.8
IA          3046355            149                  48.9
VT           625741             27                  43.1
HI          1360301             47                  34.6
ND           672591             22                  32.7
--snip--
SC          4625364             55                  11.9
LA          4533372             49                  10.8
```

```
AZ          6392017             37                  5.8
DC           601723              2                  3.3
WY           563626              1                  1.8
```

The results line up with what we might expect. The top states are well-known meat producers. For example, Nebraska is one of the nation's top cattle exporters, and Iowa leads the United States in pork production. Washington, D.C., and Wyoming at the bottom of the list are among those states with the fewest plants per million.

Generating Columns with Subqueries

You can also generate new columns of data with subqueries by placing a subquery in the column list after `SELECT`. Typically, you would use a single value from an aggregate. For example, the query in Listing 12-5 selects the `geo_name` and total population column `p0010001` from `us_counties_2010`, and then adds a subquery to add the median of all counties to each row in the new column `us_median`:

```
SELECT geo_name,
       p0010001 AS total_pop,
       (SELECT percentile_cont(.5) WITHIN GROUP (ORDER BY p0010001)
        FROM us_counties_2010) AS us_median
FROM us_counties_2010;
```

Listing 12-5: Adding a subquery to a column list

The first rows of the result set should look like this:

```
geo_name          st    total_pop    us_median
--------------    --    ---------    ---------
Autauga County    AL        54571        25857
Baldwin County    AL       182265        25857
Barbour County    AL        27457        25857
Bibb County       AL        22915        25857
Blount County     AL        57322        25857
--snip--
```

On its own, that repeating `us_median` value isn't very helpful because it's the same each time. It would be more interesting and useful to generate values that indicate how much each county's population deviates from the median value. Let's look at how we can use the same subquery technique to do that. Listing 12-6 builds on Listing 12-5 by adding a subquery expression after `SELECT` that calculates the difference between the population and the median for each county:

```
SELECT geo_name,
       state_us_abbreviation AS st,
       p0010001 AS total_pop,
       (SELECT percentile_cont(.5) WITHIN GROUP (ORDER BY p0010001)
        FROM us_counties_2010) AS us_median,
❶      p0010001 - (SELECT percentile_cont(.5) WITHIN GROUP (ORDER BY p0010001)
```

```
                   FROM us_counties_2010) AS diff_from_median
FROM us_counties_2010
❷ WHERE (p0010001 - (SELECT percentile_cont(.5) WITHIN GROUP (ORDER BY p0010001)
                   FROM us_counties_2010))
       BETWEEN -1000 AND 1000;
```

Listing 12-6: Using a subquery expression in a calculation

The added subquery ❶ is part of a column definition that subtracts the subquery's result from p0010001, the total population. It puts that new data in a column with an alias of diff_from_median. To make this query even more useful, we can narrow the results further to show only counties whose population falls within 1,000 of the median. This would help us identify which counties in America have close to the median county population. To do this, we repeat the subquery expression in the WHERE clause ❷ and filter results using the BETWEEN -1000 AND 1000 expression.

The outcome should reveal 71 counties with a population relatively close to the US median. Here are the first five rows of the results:

```
geo_name          st    total_pop    us_median    diff_from_median
---------------   --    ---------    ---------    ----------------
Cherokee County   AL        25989        25857                 132
Clarke County     AL        25833        25857                 -24
Geneva County     AL        26790        25857                 933
Cleburne County   AR        25970        25857                 113
Johnson County    AR        25540        25857                -317
--snip--
```

Bear in mind that subqueries add to overall query execution time; therefore, if we were working with millions of rows, we could simplify Listing 12-6 by eliminating the subquery that displays the column us_median. I've left it in this example for your reference.

Subquery Expressions

You can also use subqueries to filter rows by evaluating whether a condition evaluates as true or false. For this, we can use several standard ANSI SQL *subquery expressions*, which are a combination of a keyword with a subquery and are generally used in WHERE clauses to filter rows based on the existence of values in another table.

The PostgreSQL documentation at *https://www.postgresql.org/docs/current/static/functions-subquery.html* lists available subquery expressions, but here we'll examine the syntax for just two of them.

Generating Values for the IN Operator

The subquery expression IN (*subquery*) is like the IN comparison operator in Chapter 2 except we use a subquery to provide the list of values to check against rather than having to manually provide one. In the following example, we use a subquery to generate `id` values from a `retirees` table, and then use that list for the `IN` operator in the `WHERE` clause. The `NOT IN` expression does the opposite to find employees whose `id` value does *not* appear in `retirees`.

```
SELECT first_name, last_name
FROM employees
WHERE id IN (
    SELECT id
    FROM retirees);
```

We would expect the output to show the names of employees who have `id` values that match those in `retirees`.

NOTE *The presence of* `NULL` *values in a subquery result set will cause a query with a* `NOT IN` *expression to return no rows. If your data contains* `NULL` *values, use the* `WHERE NOT EXISTS` *expression described in the next section.*

Checking Whether Values Exist

Another subquery expression, `EXISTS (`*`subquery`*`)`, is a true/false test. It returns a value of `true` if the subquery in parentheses returns at least one row. If it returns no rows, `EXISTS` evaluates to `false`. In the following example, the query returns all names from an `employees` table as long as the subquery finds at least one value in `id` in a `retirees` table.

```
SELECT first_name, last_name
FROM employees
WHERE EXISTS (
    SELECT id
    FROM retirees);
```

Rather than return all names from `employees`, we instead could mimic the behavior of `IN` and limit names to where the subquery after `EXISTS` finds at least one corresponding `id` value in `retirees`. The following is a *correlated subquery* because the table named in the main query is referenced in the subquery.

```
SELECT first_name, last_name
FROM employees
WHERE EXISTS (
    SELECT id
    FROM retirees
    WHERE id = employees.id);
```

This approach is particularly helpful if you need to join on more than one column, which you can't do with the `IN` expression.

You can also use the NOT keyword with EXISTS. For example, to find employees with no corresponding record in retirees, you would run this query:

```
SELECT first_name, last_name
FROM employees
WHERE NOT EXISTS (
    SELECT id
    FROM retirees
    WHERE id = employees.id);
```

The technique of using NOT with EXISTS is helpful for assessing whether a data set is complete.

Common Table Expressions

Earlier in this chapter, you learned how to create derived tables by placing subqueries in a FROM clause. A second approach to creating temporary tables for querying uses the *Common Table Expression (CTE)*, a relatively recent addition to standard SQL that's informally called a "WITH clause." Using a CTE, you can define one or more tables up front with subqueries. Then you can query the table results as often as needed in a main query that follows.

Listing 12-7 shows a simple CTE called large_counties based on our Census data, followed by a query of that table. The code determines how many counties in each state have 100,000 people or more. Let's walk through the example.

```
❶ WITH
      large_counties (geo_name, st, p0010001)
  AS
      (
❷         SELECT geo_name, state_us_abbreviation, p0010001
          FROM us_counties_2010
          WHERE p0010001 >= 100000
      )
❸ SELECT st, count(*)
  FROM large_counties
  GROUP BY st
  ORDER BY count(*) DESC;
```

Listing 12-7: Using a simple CTE to find large counties

The WITH . . . AS block ❶ defines the CTE's temporary table large_counties. After WITH, we name the table and list its column names in parentheses. Unlike column definitions in a CREATE TABLE statement, we don't need to provide data types because the temporary table inherits those from the subquery ❷, which provides the data in parentheses after AS. The subquery must return the same number of columns as defined in the temporary table, but the column names don't need to match. Also, the column list is optional if you're not renaming columns, although including the list is still a good idea for clarity even if you don't rename columns.

The main query ❸ counts and groups the rows in `large_counties` by `st`, and then orders by the count in descending order. The top five rows of the results should look like this:

```
st    count
--    -----
TX       39
CA       35
FL       33
PA       31
OH       28
--snip--
```

As you can see, Texas, California, and Florida are among the states with the highest number of counties with a population of 100,000 or more.

You could find the same results using a `SELECT` query instead of a CTE, as shown here:

```
SELECT state_us_abbreviation, count(*)
FROM us_counties_2010
WHERE p0010001 >= 100000
GROUP BY state_us_abbreviation
ORDER BY count(*) DESC;
```

So why use a CTE? One reason is that by using a CTE, you can pre-stage subsets of data to feed into a larger query for more complex analysis. Also, you can reuse each table defined in a CTE in multiple places in the main query, which means you don't have to repeat the `SELECT` query each time. Another commonly cited advantage is that the code is more readable than if you performed the same operation with subqueries.

Listing 12-8 uses a CTE to rewrite the join of derived tables in Listing 12-4 (finding the states that have the most meat, egg, and poultry processing plants per million population) into a more readable format:

```
WHERE
❶    counties (st, population) AS
     (SELECT state_us_abbreviation, sum(population_count_100_percent)
      FROM us_counties_2010
      GROUP BY state_us_abbreviation),

❷    plants (st, plants) AS
     (SELECT st, count(*) AS "plants"
      FROM meat_poultry_egg_inspect
      GROUP BY st)

SELECT counties.st,
       population,
       plants,
```

```
       round((plants/population::numeric(10,1)) * 1000000, 1) AS "per_million"
❸ FROM counties JOIN plants
  ON counties.st = plants.st
  ORDER BY "per_million" DESC;
```

Listing 12-8: Using CTEs in a table join

Following the `WITH` keyword, we define two tables using subqueries. The first subquery, `counties` ❶, returns the population of each state. The second, `plants` ❷, returns the number of plants per state. With those tables defined, we join them ❸ on the `st` column in each table and calculate the rate per million. The results are identical to the joined derived tables in Listing 12-4, but Listing 12-8 is easier to read.

As another example, you can use a CTE to simplify queries with redundant code. For example, in Listing 12-6, we used a subquery with the `percentile_cont()` function in three different locations to find median county population. In Listing 12-9, we can write that subquery just once as a CTE:

```
❶ WITH us_median AS
      (SELECT percentile_cont(.5)
       WITHIN GROUP (ORDER BY p0010001) AS us_median_pop
       FROM us_counties_2010)

  SELECT geo_name,
         state_us_abbreviation AS st,
         p0010001 AS total_pop,
❷        us_median_pop,
❸        p0010001 - us_median_pop AS diff_from_median
❹ FROM us_counties_2010 CROSS JOIN us_median
❺ WHERE (p0010001 - us_median_pop)
         BETWEEN -1000 AND 1000;
```

Listing 12-9: Using CTEs to minimize redundant code

After the `WITH` keyword, we define `us_median` ❶ as the result of the same subquery used in Listing 12-6, which finds the median population using `percentile_cont()`. Then we reference `us_median` as a column on its own ❷, as part of a calculated column ❸, and in a `WHERE` clause ❺. To make the value available to every row in the `us_counties_2010` table during the `SELECT`, we use the `CROSS JOIN` ❹ you learned in Chapter 6.

This query provides identical results to those in Listing 12-6, but we only had to write the subquery once to find the median. Not only does this save time, but it also lets you revise the query more easily. For example, to find counties whose population is close to the 90th percentile, you can substitute `.9` for `.5` as input to `percentile_cont()` in just one place.

Cross Tabulations

Cross tabulations provide a simple way to summarize and compare variables by displaying them in a table layout, or matrix. In a matrix, rows represent one variable, columns represent another variable, and each cell where a row and column intersects holds a value, such as a count or percentage.

You'll often see cross tabulations, also called *pivot tables* or *crosstabs*, used to report summaries of survey results or to compare sets of variables. A frequent example happens during every election when candidates' votes are tallied by geography:

```
candidate    ward 1    ward 2    ward 3
---------    ------    ------    ------
Dirk         602       1,799     2,112
Pratt        599       1,398     1,616
Lerxst       911       902       1,114
```

In this case, the candidates' names are one variable, the wards (or city districts) are another variable, and the cells at the intersection of the two hold the vote totals for that candidate in that ward. Let's look at how to generate cross tabulations.

Installing the crosstab() Function

Standard ANSI SQL doesn't have a crosstab function, but PostgreSQL does as part of a *module* you can install easily. Modules include PostgreSQL extras that aren't part of the core application; they include functions related to security, text search, and more. You can find a list of PostgreSQL modules at *https://www.postgresql.org/docs/current/static/contrib.html.*

PostgreSQL's `crosstab()`function is part of the `tablefunc` module. To install `tablefunc` in the pgAdmin Query Tool, execute this command:

```
CREATE EXTENSION tablefunc;
```

PostgreSQL should return the message `CREATE EXTENSION` when it's done installing. (If you're working with another database management system, check the documentation to see whether it offers a similar functionality. For example, Microsoft SQL Server has the `PIVOT` command.)

Next, we'll create a basic crosstab so you can learn the syntax, and then we'll handle a more complex case.

Tabulating Survey Results

Let's say your company needs a fun employee activity, so you coordinate an ice cream social at your three offices in the city. The trouble is, people are particular about ice cream flavors. To choose flavors people will like, you decide to conduct a survey.

The CSV file *ice_cream_survey.csv* contains 200 responses to your survey. You can download this file, along with all the book's resources, at *https://www.nostarch.com/practicalSQL/*. Each row includes a `response_id`, `office`, and `flavor`. You'll need to count how many people chose each flavor at each office and present the results in a readable way to your colleagues.

In your `analysis` database, use the code in Listing 12-10 to create a table and load the data. Make sure you change the file path to the location on your computer where you saved the CSV file.

```
CREATE TABLE ice_cream_survey (
    response_id integer PRIMARY KEY,
    office varchar(20),
    flavor varchar(20)
);

COPY ice_cream_survey
FROM 'C:\YourDirectory\ice_cream_survey.csv'
WITH (FORMAT CSV, HEADER);
```

Listing 12-10: Creating and filling the `ice_cream_survey` *table*

If you want to inspect the data, run the following to view the first five rows:

```
SELECT *
FROM ice_cream_survey
LIMIT 5;
```

The data should look like this:

```
response_id    office      flavor
-----------    --------    ----------
          1    Uptown      Chocolate
          2    Midtown     Chocolate
          3    Downtown    Strawberry
          4    Uptown      Chocolate
          5    Midtown     Chocolate
```

It looks like chocolate is in the lead! But let's confirm this choice by using the code in Listing 12-11 to generate a crosstab from the table:

```
  SELECT *
❶ FROM crosstab('SELECT office❷,
                        flavor❸,
                        count(*)❹
                 FROM ice_cream_survey
                 GROUP BY office, flavor
                 ORDER BY office',

❺               'SELECT flavor
                 FROM ice_cream_survey
                 GROUP BY flavor
```

```
                ORDER BY flavor')

❻ AS (office varchar(20),
      chocolate bigint,
      strawberry bigint,
      vanilla bigint);
```

Listing 12-11: Generating the ice cream survey crosstab

The query begins with a `SELECT *` statement that selects everything `FROM` the contents of the `crosstab()` function ❶. We place two subqueries inside the `crosstab()` function. The first subquery generates the data for the crosstab and has three required columns. The first column, `office` ❷, supplies the row names for the crosstab, and the second column, `flavor` ❸, supplies the category columns. The third column supplies the values for each cell where row and column intersect in the table. In this case, we want the intersecting cells to show a `count()` ❹ of each flavor selected at each office. This first subquery on its own creates a simple aggregated list.

The second subquery ❺ produces the set of category names for the columns. The `crosstab()` function requires that the second subquery return only one column, so here we `SELECT` and `GROUP BY flavor`.

Then we specify the names and data types of the crosstab's output columns following the `AS` keyword ❻. The list must match the row and column names in the order the subqueries generate them. For example, because the second subquery that supplies the category columns orders the flavors alphabetically, the output column list does as well.

When we run the code, our data displays in a clean, readable crosstab:

```
office     chocolate   strawberry   vanilla
--------   ---------   ----------   -------
Downtown          23           32        19
Midtown           41                     23
Uptown            22           17        23
```

It's easy to see at a glance that the Midtown office favors chocolate but has no interest in strawberry, which is represented by a `NULL` value showing that strawberry received no votes. But strawberry is the top choice Downtown, and the Uptown office is more evenly split among the three flavors.

Tabulating City Temperature Readings

Let's create another crosstab, but this time we'll use real data. The *temperature_readings.csv* file, also available with all the book's resources, contains a year's worth of daily temperature readings from three observation stations around the United States: Chicago, Seattle, and Waikiki, Hawaii. The data come from the US National Oceanic and Atmospheric Administration (NOAA) at *https://www.ncdc.noaa.gov/cdo-web/datatools/findstation/*.

Each row in the CSV file contains four values: the station name, the date, the day's maximum temperature, and the day's minimum temperature. For each month in each city, we want to calculate the median high temperature so we can compare climates. Listing 12-12 contains the code to create the `temperature_readings` table and import the CSV file:

```
CREATE TABLE temperature_readings (
    reading_id bigserial,
    station_name varchar(50),
    observation_date date,
    max_temp integer,
    min_temp integer
);

COPY temperature_readings
     (station_name, observation_date, max_temp, min_temp)
FROM 'C:\YourDirectory\temperature_readings.csv'
WITH (FORMAT CSV, HEADER);
```

Listing 12-12: Creating and filling a `temperature_readings` *table*

The table contains the four columns from the CSV file along with an added `reading_id` of type `bigserial` that we use as a surrogate primary key. If you perform a quick count on the table, you should have 1,077 rows. Now, let's see what cross tabulating the data does using Listing 12-13:

```
SELECT *
FROM crosstab('SELECT
               station_name❶,
               date_part(''month'', observation_date)❷,
               percentile_cont(.5)❸
                   WITHIN GROUP (ORDER BY max_temp)
               FROM temperature_readings
               GROUP BY station_name,
                        date_part(''month'', observation_date)
               ORDER BY station_name',

           'SELECT month
            FROM generate_series(1,12) month')❹

AS (station varchar(50),
    jan numeric(3,0),
    feb numeric(3,0),
    mar numeric(3,0),
    apr numeric(3,0),
    may numeric(3,0),
    jun numeric(3,0),
    jul numeric(3,0),
    aug numeric(3,0),
    sep numeric(3,0),
    oct numeric(3,0),
    nov numeric(3,0),
    dec numeric(3,0)
);
```

Listing 12-13: Generating the temperature readings crosstab

The structure of the crosstab is the same as in Listing 12-11. The first subquery inside the `crosstab()` function generates the data for the crosstab, calculating the median maximum temperature for each month. It supplies the three required columns. The first column, `station_name` ❶, names the rows. The second column uses the `date_part()` function ❷ you learned in Chapter 11 to extract the month from `observation_date`, which provides the crosstab columns. Then we use `percentile_cont(.5)` ❸ to find the 50th percentile, or the median, of the `max_temp`. We group by station name and month so we have a median `max_temp` for each month at each station.

As in Listing 12-11, the second subquery produces the set of category names for the columns. I'm using a function called `generate_series()` ❹ in a manner noted in the official PostgreSQL documentation to create a list of numbers from 1 to 12 that match the month numbers `date_part()` extracts from `observation_date`.

Following `AS`, we provide the names and data types for the crosstab's output columns. Each is a `numeric` type, matching the output of the percentile function. The following output is practically poetry:

```
station                          jan  feb  mar  apr  may  jun  jul  aug  sep  oct  nov  dec
------------------------------   ---  ---  ---  ---  ---  ---  ---  ---  ---  ---  ---  ---
CHICAGO NORTHERLY ISLAND IL US    34   36   46   50   66   77   81   80   77   65   57   35
SEATTLE BOEING FIELD WA US        50   54   56   64   66   71   76   77   69   62   55   42
WAIKIKI 717.2 HI US               83   84   84   86   87   87   88   87   87   86   84   82
```

We've transformed a raw set of daily readings into a compact table showing the median maximum temperature each month for each station. You can see at a glance that the temperature in Waikiki is consistently balmy, whereas Chicago's median high temperatures vary from just above freezing to downright pleasant. Seattle falls between the two.

Crosstabs do take time to set up, but viewing data sets in a matrix often makes comparisons easier than viewing the same data in a vertical list. Keep in mind that the `crosstab()` function is CPU-intensive, so tread carefully when querying sets that have millions or billions of rows.

Reclassifying Values with CASE

The ANSI Standard SQL `CASE` statement is a *conditional expression*, meaning it lets you add some "if this, then . . ." logic to a query. You can use `CASE` in multiple ways, but for data analysis, it's handy for reclassifying values into categories. You can create categories based on ranges in your data and classify values according to those categories.

The `CASE` syntax follows this pattern:

```
❶ CASE WHEN condition THEN result
❷     WHEN another_condition THEN result
❸     ELSE result
❹ END
```

We give the `CASE` keyword ❶, and then provide at least one `WHEN` *`condition`* `THEN` *`result`* clause, where *`condition`* is any expression the database can evaluate as `true` or `false`, such as `county = 'Dutchess County'` or `date > '1995-08-09'`. If the condition is `true`, the `CASE` statement returns the *`result`* and stops checking any further conditions. The result can be any valid data type. If the condition is false, the database moves on to evaluate the next condition.

To evaluate more conditions, we can add optional `WHEN . . . THEN` clauses ❷. We can also provide an optional `ELSE` clause ❸ to return a result in case no condition evaluates as `true`. Without an `ELSE` clause, the statement would return a `NULL` when no conditions are `true`. The statement finishes with an `END` keyword ❹.

Listing 12-14 shows how to use the `CASE` statement to reclassify the temperature readings data into descriptive groups (named according to my own bias against cold weather):

```
SELECT max_temp,
       CASE WHEN max_temp >= 90 THEN 'Hot'
            WHEN max_temp BETWEEN 70 AND 89 THEN 'Warm'
            WHEN max_temp BETWEEN 50 AND 69 THEN 'Pleasant'
            WHEN max_temp BETWEEN 33 AND 49 THEN 'Cold'
            WHEN max_temp BETWEEN 20 AND 32 THEN 'Freezing'
            ELSE 'Inhumane'
        END AS temperature_group
FROM temperature_readings;
```

Listing 12-14: Reclassifying temperature data with `CASE`

We create five ranges for the `max_temp` column in `temperature_readings`, which we define using comparison operators. `CASE` evaluates each value to find whether any of the five expressions are `true`. If so, the statement outputs the appropriate text. Note that the ranges account for all possible values in the column, leaving no gaps. If none of the statements is `true`, then the `ELSE` clause assigns the value to the category `Inhumane`. The way I've structured the ranges, this happens only when `max_temp` is below 20 degrees. Alternatively, we could replace `ELSE` with a `WHEN` clause that looks for temperatures less than or equal to 19 degrees by using `max_temp <= 19`.

Run the code; the first five rows of output should look like this:

```
max_temp    temperature_group
--------    -----------------
      31    Freezing
      34    Cold
      32    Freezing
      32    Freezing
      34    Cold
      --snip--
```

Now that we've collapsed the data set into six categories, let's use those categories to compare climate among the three cities in the table.

Using CASE in a Common Table Expression

The operation we performed with `CASE` on the temperature data in the previous section is a good example of a preprocessing step you would use in a CTE. Now that we've grouped the temperatures in categories, let's count the groups by city in a CTE to see how many days of the year fall into each temperature category.

Listing 12-15 shows the code for reclassifying the daily maximum temperatures recast to generate a `temps_collapsed` CTE and then use it for an analysis:

```
❶ WITH temps_collapsed (station_name, max_temperature_group) AS
    (SELECT station_name,
           CASE WHEN max_temp >= 90 THEN 'Hot'
                WHEN max_temp BETWEEN 70 AND 89 THEN 'Warm'
                WHEN max_temp BETWEEN 50 AND 69 THEN 'Pleasant'
                WHEN max_temp BETWEEN 33 AND 49 THEN 'Cold'
                WHEN max_temp BETWEEN 20 AND 32 THEN 'Freezing'
                ELSE 'Inhumane'
            END
    FROM temperature_readings)

SELECT station_name, max_temperature_group, count(*)
❷ FROM temps_collapsed
GROUP BY station_name, max_temperature_group
ORDER BY station_name, count(*) DESC;
```

Listing 12-15: Using `CASE` in a CTE

This code reclassifies the temperatures, and then counts and groups by station name to find general climate classifications of each city. The `WITH` keyword defines the CTE of `temps_collapsed` ❶, which has two columns: `station_name` and `max_temperature_group`. We then run a `SELECT` query on the CTE ❷, performing a straightforward `count(*)` and `GROUP BY` on both columns. The results should look like this:

```
station_name                      max_temperature_group    count
------------------------------    ---------------------    -----
CHICAGO NORTHERLY ISLAND IL US    Warm                       133
CHICAGO NORTHERLY ISLAND IL US    Cold                        92
CHICAGO NORTHERLY ISLAND IL US    Pleasant                    91
CHICAGO NORTHERLY ISLAND IL US    Freezing                    30
CHICAGO NORTHERLY ISLAND IL US    Inhumane                     8
CHICAGO NORTHERLY ISLAND IL US    Hot                          8
SEATTLE BOEING FIELD WA US        Pleasant                   198
SEATTLE BOEING FIELD WA US        Warm                        98
SEATTLE BOEING FIELD WA US        Cold                        50
SEATTLE BOEING FIELD WA US        Hot                          3
WAIKIKI 717.2 HI US               Warm                       361
WAIKIKI 717.2 HI US               Hot                          5
```

Using this classification scheme, the amazingly consistent Waikiki weather, with `Warm` temperatures 361 days of the year, confirms its appeal as a vacation destination. From a temperature standpoint, Seattle looks good too, with nearly 300 days of high temps categorized as `Pleasant` or `Warm` (although this belies Seattle's legendary rainfall). Chicago, with 30 days of `Freezing` max temps and eight days `Inhumane`, probably isn't for me.

Wrapping Up

In this chapter, you learned to make queries work harder for you. You can now add subqueries in multiple locations to provide finer control over filtering or preprocessing data before analyzing it in a main query. You also can visualize data in a matrix using cross tabulations and reclassify data into groups; both techniques give you more ways to find and tell stories using your data. Great work!

Throughout the next chapters, we'll dive into SQL techniques that are more specific to PostgreSQL. We'll begin by working with and searching text and strings.

Try It Yourself

Here are two tasks to help you become more familiar with the concepts introduced in the chapter:

1. Revise the code in Listing 12-15 to dig deeper into the nuances of Waikiki's high temperatures. Limit the `temps_collapsed` table to the Waikiki maximum daily temperature observations. Then use the `WHEN` clauses in the `CASE` statement to reclassify the temperatures into seven groups that would result in the following text output:

```
'90 or more'
'88-89'
'86-87'
'84-85'
'82-83'
'80-81'
'79 or less'
```

2. In which of those groups does Waikiki's daily maximum temperature fall most often?
3. Revise the ice cream survey crosstab in Listing 12-11 to flip the table. In other words, make `flavor` the rows and `office` the columns. Which elements of the query do you need to change? Are the counts different?

13

MINING TEXT TO FIND MEANINGFUL DATA

Although it might not be obvious at first glance, you can extract data and even quantify data from text in speeches, reports, press releases, and other documents. Even though most text exists as *unstructured* or *semi-structured data*, which is not organized in rows and columns, as in a table, you can use SQL to derive meaning from it.

One way to do this is to transform the text into *structured data*. You search for and extract elements, such as dates or codes from the text, load them into a table, and analyze them. Another way to find meaning from textual data is to use advanced text analysis features, such as PostgreSQL's full-text search. Using these techniques, ordinary text can reveal facts or trends that might otherwise remain hidden.

In this chapter, you'll learn how to use SQL to analyze and transform text. You'll start with simple text wrangling using string formatting and pattern matching before moving on to more advanced analysis functions. We'll use two data sets as examples: a small collection of crime reports from a sheriff's department near Washington, D.C., and a set of State of the Union addresses delivered by former US presidents.

Formatting Text Using String Functions

Whether you're looking for data in text or simply want to change how it looks in a report, you first need to transform it into a format you can use. PostgreSQL has more than 50 built-in string functions that handle routine but necessary tasks, such as uppercasing letters, combining strings, and removing unwanted spaces. Some are part of the ANSI SQL standard, and others are PostgreSQL-only. You'll find a complete list of string functions at *https://www.postgresql.org/docs/current/static/functions-string.html*, but in this section we'll examine several that you'll likely use most often.

You can use these functions inside a variety of queries. Let's try one now using a simple query that places a function after `SELECT` and runs it in the pgAdmin Query Tool, like this: `SELECT upper('hello');`. Examples of each function plus code for all the listings in this chapter are available at *https://www.nostarch.com/practicalSQL/*.

Case Formatting

The capitalization functions format the text's case. The `upper(`*`string`*`)` function capitalizes all alphabetical characters of a string passed to it. Nonalphabet characters, such as numbers, remain unchanged. For example, `upper('Neal7')` returns `NEAL7`. The `lower(`*`string`*`)` function lowercases all alphabetical characters while keeping nonalphabet characters unchanged. For example, `lower('Randy')` returns `randy`.

The `initcap(`*`string`*`)` function capitalizes the first letter of each word. For example, `initcap('at the end of the day')` returns `At The End Of The Day`. This function is handy for formatting titles of books or movies, but because it doesn't recognize acronyms, it's not always the perfect solution. For example, `initcap('Practical SQL')` would return `Practical Sql`, because it doesn't recognize SQL as an acronym.

The `upper()` and `lower()` functions are ANSI SQL standard commands, but `initcap()` is PostgreSQL-specific. These three functions give you enough options to rework a column of text into the case you prefer. Note that capitalization does not work with all locales or languages.

Character Information

Several functions return data about the string rather than transforming it. These functions are helpful on their own or combined with other functions. For example, the `char_length(`*`string`*`)` function returns the number of characters in a string, including any spaces. For example, `char_length(' Pat ')` returns a value of `5`, because the three letters in `Pat` and the two spaces on either end total five characters. You can also use the non-ANSI SQL function `length(`*`string`*`)` to count strings, which has a variant that lets you count the length of binary strings.

NOTE *The* `length()` *function can return a different value than* `char_length()` *when used with multi-byte encodings, such as character sets covering the Chinese, Japanese, or Korean languages.*

The `position(`*`substring`*` in `*`string`*`)` function returns the location of the substring characters in the string. For example, `position(', ' in 'Tan, Bella')` returns `4`, because the comma and space characters (`, `) specified in the substring passed as the first parameter start at the fourth index position in the main string `Tan, Bella`.

Both `char_length()` and `position()` are in the ANSI SQL standard.

Removing Characters

The `trim(`*`characters`*` from `*`string`*`)` function removes unwanted characters from strings. To declare one or more characters to remove, add them to the function followed by the keyword `from` and the main string you want to change. Options to remove `leading` characters (at the front of the string), `trailing` characters (at the end of the string), or `both` make this function super flexible.

For example, `trim('s' from 'socks')` removes all `s` characters and returns `ock`. To remove only the `s` at the end of the string, add the `trailing` keyword before the character to trim: `trim(trailing 's' from 'socks')` returns `sock`.

If you don't specify any characters to remove, `trim()` removes any spaces in the string by default. For example, `trim(' Pat ')` returns `Pat` without the leading or trailing spaces. To confirm the length of the trimmed string, we can nest `trim()` inside `char_length()` like this:

```
SELECT char_length(trim(' Pat '));
```

This query should return `3`, the number of letters in `Pat`, which is the result of `trim(' Pat ')`.

The `ltrim(`*`string`*`, `*`characters`*`)` and `rtrim(`*`string`*`, `*`characters`*`)` functions are PostgreSQL-specific variations of the `trim()` function. They remove characters from the left or right ends of a string. For example, `rtrim('socks', 's')` returns `sock` by removing only the `s` on the right end of the string.

Extracting and Replacing Characters

The `left(`*`string`*`, `*`number`*`)` and `right(`*`string`*`, `*`number`*`)` functions, both ANSI SQL standard, extract and return selected characters from a string. For example, to get just the `703` area code from the phone number `703-555-1212`, use `left('703-555-1212', 3)` to specify that you want the first three characters of the string starting from the left. Likewise, `right('703-555-1212', 8)` returns eight characters from the right: `555-1212`.

To substitute characters in a string, use the `replace(string, from, to)` function. To change `bat` to `cat`, for example, you would use `replace('bat', 'b', 'c')` to specify that you want to replace the `b` in `bat` with a `c`.

Now that you know basic functions for manipulating strings, let's look at how to match more complex patterns in text and turn those patterns into data we can analyze.

Matching Text Patterns with Regular Expressions

Regular expressions (or *regex*) are a type of notational language that describes text patterns. If you have a string with a noticeable pattern (say, four digits followed by a hyphen and then two more digits), you can write a regular expression that describes the pattern. You can then use the notation in a `WHERE` clause to filter rows by the pattern or use regular expression functions to extract and wrangle text that contains the same pattern.

Regular expressions can seem inscrutable for beginning programmers; they take practice to comprehend because they use single-character symbols that aren't intuitive. Getting an expression to match a pattern can involve trial and error, and each programming language has subtle differences in the way it handles regular expressions. Still, learning regular expressions is a good investment because you gain superpower-like abilities to search text using many programming languages, text editors, and other applications.

In this section, I'll provide enough regular expression basics to work through the exercises. To learn more, I recommend interactive online code testers, such as *https://regexr.com/* or *http://www.regexpal.com/*, which have notation references.

Regular Expression Notation

Matching letters and numbers using regular expression notation is straightforward because letters and numbers (and certain symbols) are literals that indicate the same characters. For example, `Al` matches the first two characters in `Alicia`.

For more complex patterns, you'll use combinations of the regular expression elements in Table 13-1.

Table 13-1: Regular Expression Notation Basics

Expression	Description
`.`	A dot is a wildcard that finds any character except a newline.
`[FGz]`	Any character in the square brackets. Here, F, G, or z.
`[a-z]`	A range of characters. Here, lowercase a to z.
`[^a-z]`	The caret negates the match. Here, not lowercase a to z.
`\w`	Any word character or underscore. Same as [A-Za-z0-9_]
`\d`	Any digit.

`\s`	A space.
`\t`	Tab character.
`\n`	Newline character.
`\r`	Carriage return character.
`^`	Match at the start of a string.
`$`	Match at the end of a string.
`?`	Get the preceding match zero or one time.
`*`	Get the preceding match zero or more times.
`+`	Get the preceding match one or more times.
`{m}`	Get the preceding match exactly *m* times.
`{m,n}`	Get the preceding match between *m* and *n* times.
`a|b`	The pipe denotes alternation. Find either *a* or *b*.
`( )`	Create and report a capture group or set precedence.
`(?: )`	Negate the reporting of a capture group.

Using these basic regular expressions, you can match various kinds of characters and also indicate how many times and where to match them. For example, placing characters inside square brackets (`[]`) lets you match any single character or a range. So, `[FGz]` matches a single `F`, `G`, or `z`, whereas `[A-Za-z]` will match any uppercase or lowercase letter.

The backslash (`\`) precedes a designator for special characters, such as a tab (`\t`), digit (`\d`), or newline (`\n`), which is a line ending character in text files.

There are several ways to indicate how many times to match a character. Placing a number inside curly brackets indicates you want to match it that many times. For example, `\d{4}` matches four digits in a row, and `\d{1,4}` matches a digit between one and four times.

The `?`, `*`, and `+` characters provide a useful shorthand notation for number of matches. For example, the plus sign (`+`) after a character indicates to match it one or more times. So, the expression `a+` would find the `aa` characters in the name of actor Peter Sarsgaard.

Additionally, parentheses indicate a *capture group*, which you can use to specify just a portion of the matched text to display in the query results. This is useful for reporting back just a part of a matched expression. For example, if you were hunting for an `HH:MM:SS` time format in text and wanted to report only the hour, you could use an expression such as `(\d{2}):\d{2}:\d{2}`. This looks for two digits (`\d{2}`) of the hour followed by a colon, another two digits for the minutes and a colon, and then the two-digit seconds (`\d{2}`). By placing the first `\d{2}` inside parentheses, the expression will return only those two digits, even though the entire expression matches the full time.

Table 13-2 shows examples of combining regular expressions to capture different portions of the sentence "The game starts at 7 p.m. on May 7, 2017."

Table 13-2: Regular Expression Matching Examples

Expression	What it matches	Result
`.+`	Any character one or more times	`The game starts at 7 p.m. on May 2, 2017.`
`\d{1,2} (?:a.m.|p.m.)`	One or two digits followed by a space and a.m. or p.m. in a noncapture group	The game starts at `7 p.m.` on May 2, 2017.
`^\w+`	One or more word characters at the start	`The` game starts at 7 p.m. on May 2, 2017.
`\w+.$`	One or more word characters followed by any character at the end	The game starts at 7 p.m. on May 2, `2017.`
`May|June`	Either of the words May or June.	The game starts at 7 p.m. on `May` 2, 2017.
`\d{4}`	Four digits	The game starts at 7 p.m. on May 2, `2017`.
`May \d, \d{4}`	May followed by a space, digit, comma, space, and four digits	The game starts at 7 p.m. on `May 2, 2017`.

These results show the usefulness of regular expressions for selecting only the parts of the string that interest us. For example, to find the time, we use the expression `\d{1,2} (?:a.m.|p.m.)`, to look for either one or two digits because the time could be a single or double digit followed by a space. Then we look for either `a.m.` or `p.m.`; the pipe symbol separating the terms indicates the either-or condition, and placing them in parentheses separates the logic from the rest of the expression. We need the `?:` symbol to indicate that we don't want to treat the terms inside the parentheses as a capture group, which would report only `a.m.` or `p.m`. The `?:` ensures that the full match will be returned.

You can use any of these regular expressions in pgAdmin by placing the text and regular expression inside the `substring(`*`string`*` from `*`pattern`*`)` function to return the matched text. For example, to find the four-digit year, use the following query:

```
SELECT substring('The game starts at 7 p.m. on May 2, 2017.' from '\d{4}');
```

This query should return `2017`, because we specified that the pattern should look for any digit that is four characters long, and 2017 is the only digit in this string that matches these criteria. You can check out sample `substring()` queries for all the examples in Table 13-2 in the book's code resources at *https://www.nostarch.com/practicalSQL/*.

The lesson here is that if you can identify a pattern in the text, you can use a combination of regular expression symbols to locate it. This technique is particularly useful when you have repeating patterns in text that you want to turn into a set of data to analyze. Let's practice how to use regular expression functions using a real-world example.

Turning Text to Data with Regular Expression Functions

A sheriff's department in one of the Washington, D.C., suburbs publishes daily reports that detail the date, time, location, and description of incidents the department investigates. These reports would be great to analyze except they post the information in Microsoft Word documents saved as PDF files, which is not the friendliest format for importing into a database.

If I copy and paste incidents from the PDF into a text editor, the result is blocks of text that look something like Listing 13-1:

```
❶ 4/16/17-4/17/17
❷ 2100-0900 hrs.
❸ 46000 Block Ashmere Sq.
❹ Sterling
❺ Larceny: ❻ The victim reported that a
  bicycle was stolen from their opened
  garage door during the overnight hours.
❼ C0170006614

  04/10/17
  1605 hrs.
  21800 block Newlin Mill Rd.
  Middleburg
  Larceny: A license plate was reported
  stolen from a vehicle.
  SO170006250
```

Listing 13-1: Crime reports text

Each block of text includes dates ❶, times ❷, a street address ❸, city or town ❹, the type of crime ❺, and a description ❻ of the incident. The last piece of information is a code ❼ that might be a unique ID for the incident, although we'd have to check with the sheriff's department to be sure. There are slight inconsistencies. For example, the first block of text has two dates (`4/16/17-4/17/17`) and two times (`2100-0900 hrs.`), meaning the exact time of the incident is unknown and likely occurred within that time span. The second block has one date and time.

If you compile these reports regularly, you can expect to find some good insights that could answer important questions: where do crimes tend to occur? Which crime types occur most frequently? Do they happen more often on weekends or weekdays? Before you can start answering these questions, you'll need to extract the text into table columns using regular expressions.

Creating a Table for Crime Reports

I've collected five of the crime incidents into a file named *crime_reports.csv* that you can download at *https://www.nostarch.com/practicalSQL/*. Download the file and save it on your computer. Then use the code in Listing 13-2 to build a table that has a column for each data element you can parse from the text using a regular expression.

```
CREATE TABLE crime_reports (
    crime_id bigserial PRIMARY KEY,
    date_1 timestamp with time zone,
    date_2 timestamp with time zone,
    street varchar(250),
    city varchar(100),
    crime_type varchar(100),
    description text,
    case_number varchar(50),
    original_text text NOT NULL
);

COPY crime_reports (original_text)
FROM 'C:\YourDirectory\crime_reports.csv'
WITH (FORMAT CSV, HEADER OFF, QUOTE '"');
```

Listing 13-2: Creating and loading the `crime_reports` table

Run the `CREATE TABLE` statement in Listing 13-2, and then `COPY` to load the text into the column `original_text`. The rest of the columns will be `NULL` until we fill them.

When you run `SELECT original_text FROM crime_reports;` in pgAdmin, the results grid should display five rows and the first several words of each report. When you hover your cursor over any cell, pgAdmin shows all the text in that row, as shown in Figure 13-1.

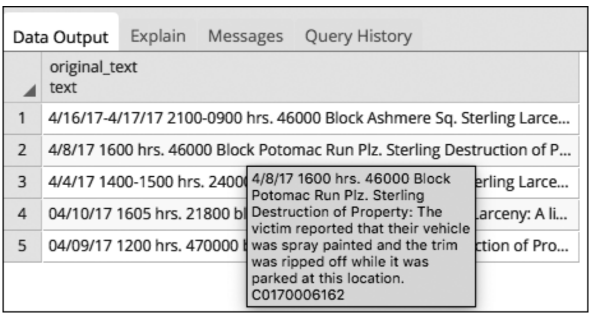


Figure 13-1: Displaying additional text in the pgAdmin results grid

Now that you've loaded the text you'll be parsing, let's explore this data using PostgreSQL regular expression functions.

Matching Crime Report Date Patterns

The first piece of data we want to extract from the report `original_text` is the date or dates of the crime. Most of the reports have one date, although one has two. The reports also have associated times, and we'll combine the extracted date and time into a timestamp. We'll fill `date_1` with the first (or only) date and time in each report. In cases where a second date or second time exists, we'll create a timestamp and add it to `date_2`.

For extracting data, we'll use the `regexp_match(`*`string, pattern`*`)` function, which is similar to `substring()` with a few exceptions. One is that it returns each match as text in an array. Also, if there are no matches, it returns `NULL`. As you might recall from Chapter 5, arrays are a list of elements; in one exercise, you used an array to pass a list of values into the `percentile_cont()` function to calculate quartiles. I'll show you how to work with results that come back as an array when we parse the crime reports.

NOTE *The `regexp_match()` function was introduced in PostgreSQL 10 and is not available in earlier versions.*

To start, let's use `regexp_match()` to find dates in each of the five incidents in `crime_reports`. The general pattern to match is *`MM/DD/YY`*, although there may be one or two digits for both the month and date. Here's a regular expression that matches the pattern:

```
\d{1,2}\/\d{1,2}\/\d{2}
```

In this expression, `\d{1,2}` indicates the month. The numbers inside the curly brackets specify that you want at least one digit and at most two digits. Next, you want to look for a forward slash (/), but because a forward slash can have special meaning in regular expressions, you must *escape* that character by placing a backslash (\) in front of it, like this `\/`. Escaping a character in this context simply means we want to treat it as a literal rather than letting it take on special meaning. So, the combination of the backslash and forward slash (`\/`) indicates you want a forward slash.

Another `\d{1,2}` follows for a single- or double-digit day of the month. The expression ends with a second escaped forward slash and `\d{2}` to indicate the two-digit year. Let's pass the expression `\d{1,2}\/\d{1,2}\/\d{2}` to `regexp_match()`, as shown in Listing 13-3:

```
SELECT crime_id,
       regexp_match(original_text, '\d{1,2}\/\d{1,2}\/\d{2}')
FROM crime_reports;
```

Listing 13-3: Using `regexp_match()` to find the first date

Run that code in pgAdmin, and the results should look like this:

```
crime_id    regexp_match
--------    ------------
       1    {4/16/17}
       2    {4/8/17}
       3    {4/4/17}
       4    {04/10/17}
       5    {04/09/17}
```

Note that each row shows the first date listed for the incident, because `regexp_match()` returns the first match it finds by default. Also note that each date is enclosed in curly brackets. That's PostgreSQL indicating that `regexp_match()` returns each result in an array, or list of elements. Later in "Extracting Text from the `regexp_match()` Result" on page 224, I'll show you how to access those elements from the array. You can also read more about using arrays in PostgreSQL at *https://www.postgresql.org/docs/current/static/arrays.html*.

Matching the Second Date When Present

We've successfully extracted the first date from each report. But recall that one of the five incidents has a second date. To find and display all the dates in the text, you must use the related `regexp_matches()` function and pass in an option in the form of the flag `g` ❶, as shown in Listing 13-4.

```
SELECT crime_id,
       regexp_matches(original_text, '\d{1,2}\/\d{1,2}\/\d{2}', 'g'❶)
FROM crime_reports;
```

Listing 13-4: Using the `regexp_matches()` function with the `'g'` flag

The `regexp_matches()` function, when supplied the `g` flag, differs from `regexp_match()` by returning each match the expression finds as a row in the results rather than returning just the first match.

Run the code again with this revision; you should now see two dates for the incident that has a `crime_id` of `1`, like this:

```
crime_id    regexp_matches
--------    --------------
       1    {4/16/17}
       1    {4/17/17}
       2    {4/8/17}
       3    {4/4/17}
       4    {04/10/17}
       5    {04/09/17}
```

Any time a crime report has a second date, we want to load it and the associated time into the `date_2` column. Although adding the `g` flag shows us all the dates, to extract just the second date in a report, we can use the pattern we always see when two dates exist. In Listing 13-1, the first block of text showed the two dates separated by a hyphen, like this:

```
4/16/17-4/17/17
```

This means you can switch back to `regexp_match()` and write a regular expression to look for a hyphen followed by a date, as shown in Listing 13-5:

```
SELECT crime_id,
       regexp_match(original_text, '-\d{1,2}\/\d{1,2}\/\d{2}')
FROM crime_reports;
```

Listing 13-5: Using `regexp_match()` to find the second date

Although this query finds the second date in the first item (and returns a `NULL` for the rest), there's an unintended consequence: it displays the hyphen along with it.

```
crime_id    regexp_match
--------    ------------
       1    {-4/17/17}
       2
       3
       4
       5
```

You don't want to include the hyphen, because it's an invalid format for the `timestamp` data type. Fortunately, you can specify the exact part of the regular expression you want to return by placing parentheses around it to create a capture group, like this:

```
-(\d{1,2}/\d{1,2}/\d{1,2})
```

This notation returns only the part of the regular expression you want. Run the modified query in Listing 13-6 to report only the data in parentheses.

```
SELECT crime_id,
       regexp_match(original_text, '-(\d{1,2}\/\d{1,2}\/\d{1,2})')
FROM crime_reports;
```

Listing 13-6: Using a capture group to return only the date

The query in Listing 13-6 should return just the second date without the leading hyphen, as shown here:

```
crime_id    regexp_match
--------    ------------
       1    {4/17/17}
       2
       3
       4
       5
```

The process you've just completed is typical. You start with text to analyze, and then write and refine the regular expression until it produces the data you want. So far, we've created regular expressions to match the first date and a second date, if it exists. Now, let's use regular expressions to extract additional data elements.

Matching Additional Crime Report Elements

In this section, we'll capture times, addresses, crime type, description, and case number from the crime reports. Here are the expressions for capturing this information:

First hour `\/\d{2}\n(\d{4})`

The first hour, which is the hour the crime was committed or the start of the time range, always follows the date in each crime report, like this:

```
4/16/17-4/17/17
2100-0900 hrs.
```

To find the first hour, we start with an escaped forward slash and `\d{2}`, which represents the two-digit year preceding the first date (`17`). The `\n` character indicates the newline because the hour always starts on a new line, and `\d{4}` represents the four-digit hour (`2100`). Because we just want to return the four digits, we put `\d{4}` inside parentheses as a capture group.

Second hour `\/\d{2}\n\d{4}-(\d{4})`

If the second hour exists, it will follow a hyphen, so we add a hyphen and another `\d{4}` to the expression we just created for the first hour. Again, the second `\d{4}` goes inside a capture group, because `0900` is the only hour we want to return.

Street `hrs.\n(\d+ .+(?:Sq.|Plz.|Dr.|Ter.|Rd.))`

In this data, the street always follows the time's `hrs.` designation and a newline (`\n`), like this:

```
04/10/17
1605 hrs.
21800 block Newlin Mill Rd.
```

The street address always starts with some number that varies in length and ends with an abbreviated suffix of some kind. To describe this pattern, we use `\d+` to match any digit that appears one or more times. Then we specify a space and look for any character one or more times using the dot wildcard and plus sign (`.+`) notation. The expression ends with a series of terms separated by the alternation pipe symbol that looks like this: `(?:Sq.|Plz.|Dr.|Ter.|Rd.)`. The terms are inside parentheses, so the expression will match one or another of those terms. When we group terms like this, if we don't want the parentheses to act as a capture group, we need to add `?:` to negate that effect.

NOTE *In a large data set, it's likely roadway names would end with suffixes beyond the five in our regular expression. After making an initial pass at extracting the street, you can run a query to check for unmatched rows to find additional suffixes to match.*

City `(?:Sq.|Plz.|Dr.|Ter.|Rd.)\n(\w+ \w+|\w+)\n`

Because the city always follows the street suffix, we reuse the terms separated by the alternation symbol we just created for the street. We follow that with a newline (`\n`) and then use a capture group to look for two words or one word (`\w+ \w+|\w+`) before a final newline, because a town or city name can be more than a single word.

Crime type `\n(?:\w+ \w+|\w+)\n(.*):`

The type of crime always precedes a colon (the only time a colon is used in each report) and might consist of one or more words, like this:

```
--snip--
Middleburg
Larceny: A license plate was reported
stolen from a vehicle.
SO170006250
--snip--
```

To create an expression that matches this pattern, we follow a newline with a nonreporting capture group that looks for the one- or two-word city. Then we add another newline and match any character that occurs zero or more times before a colon using `(.*):`.

Description `:\s(.+)(?:C0|SO)`

The crime description always comes between the colon after the crime type and the case number. The expression starts with the colon, a space character (`\s`), and then a capture group to find any character that appears one or more times using the `.+` notation. The nonreporting capture group `(?:C0|SO)` tells the program to stop looking when it encounters either `C0` or `SO`, the two character pairs that start each case number. We have to do this because the description might have one or more line breaks.

Case number `(?:C0|SO)[0-9]+`

The case number starts with either `C0` or `SO`, followed by a set of digits. To match this pattern, the expression looks for either `C0` or `SO` in a nonreporting capture group followed by any digit from 0 to 9 that occurs one or more times using the `[0-9]` range notation.

Now let's pass these regular expressions to `regexp_match()` to see them in action. Listing 13-7 shows a sample `regexp_match()` query that retrieves the case number, first date, crime type, and city:

```
SELECT
    regexp_match(original_text, '(?:C0|SO)[0-9]+') AS case_number,
    regexp_match(original_text, '\d{1,2}\/\d{1,2}\/\d{2}') AS date_1,
    regexp_match(original_text, '\n(?:\w+ \w+|\w+)\n(.*):') AS crime_type,
    regexp_match(original_text, '(?:Sq.|Plz.|Dr.|Ter.|Rd.)\n(\w+ \w+|\w+)\n')
        AS city
FROM crime_reports;
```

Listing 13-7: Matching case number, date, crime type, and city

Run the code, and the results should look like this:

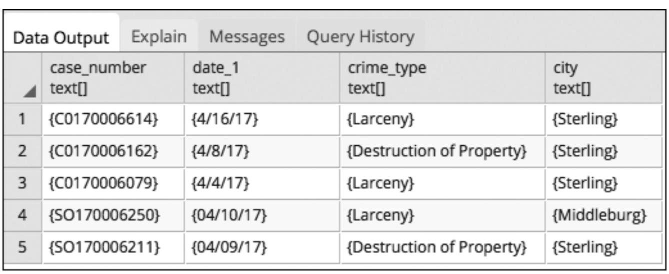
```
 case_number     date_1       crime_type                  city
-------------    ----------   -------------------------   ------------
{C0170006614}    {4/16/17}    {Larceny}                   {Sterling}
{C0170006162}    {4/8/17}     {Destruction of Property}   {Sterling}
{C0170006079}    {4/4/17}     {Larceny}                   {Sterling}
{SO170006250}    {04/10/17}   {Larceny}                   {Middleburg}
{SO170006211}    {04/09/17}   {Destruction of Property}   {Sterling}
```

After all that wrangling, we've transformed the text into a structure that is more suitable for analysis. Of course, you would have to include many more incidents to count the frequency of crime type by city or the number of crimes per month to identify any trends.

To load each parsed element into the table's columns, we'll create an `UPDATE` query. But before you can insert the text into a column, you'll need to learn how to extract the text from the array that `regexp_match()` returns.

Extracting Text from the regexp_match() Result

In "Matching Crime Report Date Patterns" on page 218, I mentioned that `regexp_match()` returns an array containing text values. Two clues reveal that these are text values. The first is that the data type designation in the column header shows `text[]` instead of `text`. The second is that each result is surrounded by curly brackets. Figure 13-2 shows how pgAdmin displays the results of the query in Listing 13-7.



	case_number text[]	date_1 text[]	crime_type text[]	city text[]
1	{C0170006614}	{4/16/17}	{Larceny}	{Sterling}
2	{C0170006162}	{4/8/17}	{Destruction of Property}	{Sterling}
3	{C0170006079}	{4/4/17}	{Larceny}	{Sterling}
4	{SO170006250}	{04/10/17}	{Larceny}	{Middleburg}
5	{SO170006211}	{04/09/17}	{Destruction of Property}	{Sterling}

Figure 13-2: Array values in the pgAdmin results grid

The `crime_reports` columns we want to update are not array types, so rather than passing in the array values returned by `regexp_match()`, we need to extract the values from the array first. We do this by using array notation, as shown in Listing 13-8.

```
SELECT
    crime_id,
 ❶ (regexp_match(original_text, '(?:C0|SO)[0-9]+'))[1]❷
        AS case_number
FROM crime_reports;
```

Listing 13-8: Retrieving a value from within an array

First, we wrap the `regexp_match()` function ❶ in parentheses. Then, at the end, we provide a value of 1, which represents the first element in the array, enclosed in square brackets ❷. The query should produce the following results:

```
crime_id    case_number
--------    -----------
       1    C0170006614
       2    C0170006162
       3    C0170006079
       4    SO170006250
       5    SO170006211
```

Now the data type designation in the pgAdmin column header should show `text` instead of `text[]`, and the values are no longer enclosed in curly brackets. We can now insert these values into `crime_reports` using an `UPDATE` query.

Updating the crime_reports Table with Extracted Data

With each element currently available as text, we can update columns in the `crime_reports` table with the appropriate data from the original crime report. To start, Listing 13-9 combines the extracted first date and time into a single `timestamp` value for the column `date_1`.

```
  UPDATE crime_reports
❶ SET date_1 =
  (
   ❷ (regexp_match(original_text, '\d{1,2}\/\d{1,2}\/\d{2}'))[1]
       ❸ || ' ' ||
   ❹ (regexp_match(original_text, '\/\d{2}\n(\d{4})'))[1]
       ❺ ||' US/Eastern'
❻ )::timestamptz;

  SELECT crime_id,
         date_1,
```

```
    original_text
FROM crime_reports;
```

Listing 13-9: Updating the `crime_reports date_1` column

Because the `date_1` column is of type `timestamp`, we must provide an input in that data type. To do that, we'll use the PostgreSQL double-pipe (`||`) concatenation operator to combine the extracted date and time in a format that's acceptable for `timestamp with time zone` input. In the `SET` clause ❶, we start with the regex pattern that matches the first date ❷. Next, we concatenate the date with a space using two single quotes ❸ and repeat the concatenation operator. This step combines the date with a space before connecting it to the regex pattern that matches the time ❹. Then we include the time zone for the Washington, D.C., area by concatenating that at the end of the string ❺ using the `US/Eastern` designation. Concatenating these elements creates a string in the pattern of *`MM/DD/YY HHMM TIMEZONE`*, which is acceptable as a `timestamp` input. We cast the string to a `timestamp with time zone` data type ❻ using the PostgreSQL double-colon shorthand and the `timestamptz` abbreviation.

When you run the `UPDATE` portion of the code, PostgreSQL should return the message `UPDATE 5`. Running the `SELECT` statement in pgAdmin should show the now-filled `date_1` column alongside a portion of the `original_text` column, like this:

```
crime_id    date_1                    original_text
--------    ----------------------    -------------------------------------
       1    2017-04-16 21:00:00-04    4/16/17-4/17/17 2100-0900 hrs. 460 ...
       2    2017-04-08 16:00:00-04    4/8/17 1600 hrs. 46000 Block Potom ...
       3    2017-04-04 14:00:00-04    4/4/17 1400-1500 hrs. 24000 Block  ...
       4    2017-04-10 16:05:00-04    04/10/17 1605 hrs. 21800 block New ...
       5    2017-04-09 12:00:00-04    04/09/17 1200 hrs. 470000 block Fa ...
```

At a glance, you can see that `date_1` accurately captures the first date and time that appears in the original text and puts it into a useable format that we can analyze. Note that if you're not in the Eastern time zone, the timestamps will instead reflect your pgAdmin client's time zone. As you learned in "Setting the Time Zone" on page 180 , you can use the command `SET timezone TO 'US/Eastern';` to change the client to reflect Eastern time.

Using CASE to Handle Special Instances

You could write an `UPDATE` statement for each remaining data element, but combining those statements into one would be more efficient. Listing 13-10 updates all the `crime_reports` columns using a single statement while handling inconsistent values in the data.

```
UPDATE crime_reports
SET date_1❶ =
    (
      (regexp_match(original_text, '\d{1,2}\/\d{1,2}\/\d{2}'))[1]
          || ' ' ||
```

```
  (regexp_match(original_text, '\/\d{2}\n(\d{4})'))[1]
      ||' US/Eastern'
):timestamptz,

date_2❷ =
CASE❸
    WHEN❹ (SELECT regexp_match(original_text, '-(\d{1,2}\/\d{1,2}\/\d{1,2})') IS NULL❺)
            AND (SELECT regexp_match(original_text, '\/\d{2}\n\d{4}-(\d{4})') IS NOT NULL❻)
    THEN❼
      ((regexp_match(original_text, '\d{1,2}\/\d{1,2}\/\d{2}'))[1]
          || ' ' ||
      (regexp_match(original_text, '\/\d{2}\n\d{4}-(\d{4})'))[1]
          ||' US/Eastern'
      )::timestamptz

    WHEN❽ (SELECT regexp_match(original_text, '-(\d{1,2}\/\d{1,2}\/\d{1,2})') IS NOT NULL)
            AND (SELECT regexp_match(original_text, '\/\d{2}\n\d{4}-(\d{4})') IS NOT NULL)
    THEN
      ((regexp_match(original_text, '-(\d{1,2}\/\d{1,2}\/\d{1,2})'))[1]
          || ' ' ||
      (regexp_match(original_text, '\/\d{2}\n\d{4}-(\d{4})'))[1]
          ||' US/Eastern'
      )::timestamptz

    ELSE NULL❾
END,
street = (regexp_match(original_text, 'hrs.\n(\d+ .+(?:Sq.|Plz.|Dr.|Ter.|Rd.))'))[1],
city = (regexp_match(original_text,
                        '(?:Sq.|Plz.|Dr.|Ter.|Rd.)\n(\w+ \w+|\w+)\n'))[1],
crime_type = (regexp_match(original_text, '\n(?:\w+ \w+|\w+)\n(.*):'))[1],
description = (regexp_match(original_text, ':\s(.+)(?:C0|SO)'))[1],
case_number = (regexp_match(original_text, '(?:C0|SO)[0-9]+'))[1];
```

Listing 13-10: Updating all `crime_reports` columns

This `UPDATE` statement might look intimidating but not if we break it down by column. First, we use the same code from Listing 13-9 to update the `date_1` column ❶. But to update `date_2` ❷, we need to account for the inconsistent presence of a second date and time. In our limited data set, there are three possibilities:

1. A second hour exists but not a second date. This occurs when a report covers a range of hours on one date.
2. A second date and second hour exist. This occurs when a report covers more than one date.
3. Neither a second date nor a second hour exists.

To insert the correct value in `date_2` for each scenario, we use the `CASE` statement syntax you learned in "Reclassifying Values with `CASE`" on page 209 to test for each possibility. After the `CASE` keyword ❸, we use a series of `WHEN ... THEN` statements to check for the first two conditions and provide the value to insert; if neither condition exists, we use an `ELSE` keyword to provide a `NULL`.

The first `WHEN` statement ❹ checks whether `regexp_match()` returns a `NULL` ❺ for the second date and a value for the second hour (using `IS NOT NULL` ❻). If that condition evaluates as `true`, the `THEN` statement ❼ concatenates the first date with the second hour to create a timestamp for the update.

The second `WHEN` statement ❽ checks that `regexp_match()` returns a value for the second hour and second date. If `true`, the `THEN` statement concatenates the second date with the second hour to create a timestamp.

If neither of the two `WHEN` statements returns true, the `ELSE` statement ❾ provides a `NULL` for the update because there is only a first date and first time.

NOTE *The `WHEN` statements handle the possibilities that exist in our small sample data set. If you are working with more data, you might need to handle additional variations, such as a second date but not a second time.*

When we run the full query in Listing 13-10, PostgreSQL should report `UPDATE 5`. Success! Now that we've updated all the columns with the appropriate data while accounting for elements that have additional data, we can examine all the columns of the table and find the parsed elements from `original_text`. Listing 13-11 queries four of the columns:

```
SELECT date_1,
       street,
       city,
       crime_type
FROM crime_reports;
```

Listing 13-11: Viewing selected crime data

The results of the query should show a nicely organized set of data that looks something like this:

```
date_1                    street                              city          crime_type
----------------------    ---------------------------------   ----------    ------------------
2017-04-16 21:00:00-04    46000 Block Ashmere Sq.             Sterling      Larceny
2017-04-08 16:00:00-04    46000 Block Potomac Run Plz.        Sterling      Destruction of ...
2017-04-04 14:00:00-04    24000 Block Hawthorn Thicket Ter.   Sterling      Larceny
2017-04-10 16:05:00-04    21800 block Newlin Mill Rd.         Middleburg    Larceny
2017-04-09 12:00:00-04    470000 block Fairway Dr.            Sterling      Destruction of ...
```

You've successfully transformed raw text into a table that can answer questions and reveal storylines about crime in this area.

The Value of the Process

Writing regular expressions and coding a query to update a table can take time, but there is value to identifying and collecting data this way. In fact, some of the best data sets you'll encounter are those you build yourself. Everyone can download the same data sets, but the ones you build are yours alone. You get to be first person to find and tell the story behind the data.

Also, after you set up your database and queries, you can use them again and again. In this example, you could collect crime reports every day (either by hand or by automating downloads using a programming language such as Python) for an ongoing data set that you can mine continually for trends.

In the next section, we'll finish our exploration of regular expressions using additional PostgreSQL functions.

Using Regular Expressions with WHERE

You've filtered queries using `LIKE` and `ILIKE` in `WHERE` clauses. In this section, you'll learn to use regular expressions in `WHERE` clauses so you can perform more complex matches.

We use a tilde (~) to make a case-sensitive match on a regular expression and a tilde-asterisk (~*) to perform a case-insensitive match. You can negate either expression by adding an exclamation point in front. For example, `!~*` indicates to *not* match the regular expression, making it case-insensitive. Listing 13-12 shows how this works using the 2010 Census `us_counties_2010` table from previous exercises:

```
SELECT geo_name
FROM us_counties_2010
❶ WHERE geo_name ~* '(.+lade.+|.+lare.+)'
ORDER BY geo_name;

SELECT geo_name
FROM us_counties_2010
❷ WHERE geo_name ~* '.+ash.+' AND geo_name !~*'Wash.+'
ORDER BY geo_name;
```

Listing 13-12: Using regular expressions in a `WHERE` clause

The first `WHERE` clause ❶ uses the tilde-asterisk (~*) to perform a case-insensitive match on the regular expression `(.+lade.+|.+lare.+)` to find any county names that contain either the letters `lade` or `lare` between other characters. The results should show eight rows:

```
geo_name
-------------------
Bladen County
Clare County
Clarendon County
Glades County
Langlade County
Philadelphia County
Talladega County
Tulare County
```

As you can see, the county names include the letters `lade` or `lare` between other characters.

The second `WHERE` clause ❷ uses the tilde-asterisk (`~*`) as well as a negated tilde-asterisk (`!~*`) to find county names containing the letters `ash` but excluding those starting with `Wash`. This query should return the following:

```
geo_name
--------------
Nash County
Wabash County
Wabash County
Wabasha County
```

All four counties in this output have names that contain the letters `ash` but don't start with `Wash`.

These are fairly simple examples, but you can do more complex matches using regular expressions that you wouldn't be able to perform with the wildcards available with just `LIKE` and `ILIKE`.

Additional Regular Expression Functions

Let's look at three more regular expression functions you might find useful when working with text. Listing 13-13 shows several regular expression functions that replace and split text:

```
❶ SELECT regexp_replace('05/12/2018', '\d{4}', '2017');

❷ SELECT regexp_split_to_table('Four,score,and,seven,years,ago', ',');

❸ SELECT regexp_split_to_array('Phil Mike Tony Steve', ',');
```

Listing 13-13: Regular expression functions to replace and split text

The `regexp_replace(`*`string`*`, `*`pattern`*`, `*`replacement text`*`)` function lets you substitute a matched pattern with replacement text. In the example at ❶, we're searching the date string `05/12/2018` for any set of four digits in a row using `\d{4}`. When found, we replace them with the replacement text `2017`. The result of that query is `05/12/2017` returned as text.

The `regexp_split_to_table(`*`string`*`, `*`pattern`*`)` function splits delimited text into rows. Listing 13-13 uses this function to split the string `Four,score,and,seven,years,ago` on commas ❷, resulting in a set of rows that has one word in each row:

```
regexp_split_to_table
---------------------
Four
score
and
seven
years
ago
```

Keep this function in mind as you tackle one of the "Try It Yourself" questions at the end of the chapter.

The `regexp_split_to_array(`*`string, pattern`*`)` function splits delimited text into an array. The example splits the string `Phil Mike Tony Steve` on spaces ❸, returning a text array that should look like this in pgAdmin:

```
regexp_split_to_array
----------------------
{Phil,Mike,Tony,Steve}
```

The `text[]` notation in pgAdmin's column header along with curly brackets around the results confirms that this is indeed an array type, which provides another means of analysis. For example, you could then use a function such as `array_length()` to count the number of words, as shown in Listing 13-14:

```
SELECT array_length(regexp_split_to_array('Phil Mike Tony Steve', ' '), 1);
```

Listing 13-14: Finding an array length

The query should return `4` because four elements are in this array. You can read more about `array_length()` and other array functions at *https://www.postgresql.org/docs/current/static/functions-array.html.*

Full Text Search in PostgreSQL

PostgreSQL comes with a powerful full text search engine that gives you more options when searching for information in large amounts of text. You're familiar with Google or other web search engines and similar technology that powers search on news websites or research databases, such as LexisNexis. Although the implementation and capability of full text search demands several chapters, here I'll walk you through a simple example of setting up a table for text search and functions for searching using PostgreSQL.

For this example, I assembled 35 speeches by former US presidents who served post-World War II through the Gerald R. Ford administration. Consisting mostly of State of the Union addresses, these public texts are available through the Internet Archive at *https://archive.org/* and the University of California's The American Presidency Project at *http://www.presidency.ucsb.edu/ws/index.php/*. You can find the data in the *sotu-1946-1977.csv* file along with the book's resources at *https://www.nostarch.com/practicalSQL/*.

Let's start with the data types unique to full text search.

Text Search Data Types

PostgreSQL's implementation of text search includes two data types. The `tsvector` data type represents the text to be searched and to be stored in an optimized form. The `tsquery` data type represents the search query terms and operators. Let's look at the details of both.

Storing Text as Lexemes with tsvector

The `tsvector` data type reduces text to a sorted list of *lexemes*, which are units of meaning in language. Think of lexemes as words without the variations created by suffixes. For example, the `tsvector` format would store the words "washes," "washed," and "washing" as the lexeme "wash" while noting each word's position in the original text. Converting text to `tsvector` also removes small *stop words* that usually don't play a role in search, such as "the" or "it."

To see how this data type works, let's convert a string to `tsvector` format. Listing 13-15 uses the PostgreSQL search function `to_tsvector()`, which normalizes the text "I am walking across the sitting room to sit with you" to lexemes:

```
SELECT to_tsvector('I am walking across the sitting room to sit with you.');
```

Listing 13-15: Converting text to `tsvector` data

Execute the code, and it should return the following output in `tsvector` format:

```
'across':4 'room':7 'sit':6,9 'walk':3
```

The `to_tsvector()` function reduces the number of words from seven to four, eliminating the words "I," "am," and "the," which are not helpful search terms. The function removes suffixes, changing "walking" to "walk" and "sitting" to "sit." It also orders the words alphabetically, and the number following each colon indicates its position in the original string, taking stop words into account. Note that "sit" is recognized as being in two positions, one for "sitting" and one for "sit."

Creating the Search Terms with tsquery

The `tsquery` data type represents the full text search query, again optimized as lexemes. It also provides operators for controlling the search. Examples of operators include the ampersand (`&`) for "and," the pipe symbol (`|`) for "or," and the exclamation point (`!`) for "not." A special `<->` operator lets you search for adjacent words or words a certain distance apart.

Listing 13-16 shows how the `to_tsquery()` function converts search terms to the `tsquery` data type.

```
SELECT to_tsquery('walking & sitting');
```

Listing 13-16: Converting search terms to `tsquery` data

After running the code, you should see that the resulting `tsquery` data type has normalized the terms into lexemes, which match the format of the data to search:

```
'walk' & 'sit'
```

Now you can use terms stored as `tsquery` to search text optimized as `tsvector`.

Using the @@ Match Operator for Searching

With the text and search terms converted to the full text search data types, you can use the double-at sign (`@@`) match operator to check whether a query matches text. The first query in Listing 13-17 uses `to_tsquery()` to search for the words "walking" and "sitting," which we combine with the ampersand "and" operator. It returns a Boolean value of `true` because both "walking" and "sitting" are present in the text converted by `to_tsvector()`.

```
SELECT to_tsvector('I am walking across the sitting room') @@ to_tsquery('walking & sitting');
SELECT to_tsvector('I am walking across the sitting room') @@ to_tsquery('walking & running');
```

Listing 13-17: Querying a `tsvector` type with a `tsquery`

However, the second query returns `false` because both "walking" and "running" are not present in the text. Now let's build a table for searching the speeches.

Create a Table for Full Text Search

Let's start by creating a table to hold the speech text. The code in Listing 13-18 creates and fills `president_speeches` so it contains a column for the original speech text as well as a column of type `tsvector`. The reason is that we need to convert the original speech text into that `tsvector` column to optimize it for searching. We can't easily do that conversion during import, so let's handle that as a separate step. Be sure to change the file path to match the location of your saved CSV file:

```
CREATE TABLE president_speeches (
    sotu_id serial PRIMARY KEY,
    president varchar(100) NOT NULL,
    title varchar(250) NOT NULL,
    speech_date date NOT NULL,
    speech_text text NOT NULL,
    search_speech_text tsvector
);

COPY president_speeches (president, title, speech_date, speech_text)
FROM 'C:\YourDirectory\sotu-1946-1977.csv'
WITH (FORMAT CSV, DELIMITER '|', HEADER OFF, QUOTE '@');
```

Listing 13-18: Creating and filling the `president_speeches` table

After executing the query, run `SELECT * FROM president_speeches;` to see the data. In pgAdmin, hover your mouse over any cell to see extra words not visible in the results grid. You should see a sizeable amount of text in each row of the `speech_text` column.

Next, we copy the contents of `speech_text` to the `tsvector` column `search_speech_text` and transform it to that data type at the same time. The `UPDATE` query in Listing 13-19 handles the task:

```
UPDATE president_speeches
❶ SET search_speech_text = to_tsvector('english', speech_text);
```

Listing 13-19: Converting speeches to `tsvector` in the `search_speech_text` column

The `SET` clause fills `search_speech_text` with the output of `to_tsvector()` ❶. The first argument in the function specifies the language for parsing the lexemes. We're using the default of `english` here, but you can substitute it with `spanish`, `german`, `french`, or whatever language you want to use (some languages may require you to find and install additional dictionaries). The second argument is the name of the input column. Run the code to fill the column.

Finally, we want to index the `search_speech_text` column to speed up searches. You learned about indexing in Chapter 7, which focused on PostgreSQL's default index type, B-Tree. For full text search, the PostgreSQL documentation recommends using the *Generalized Inverted Index (GIN)* index (see *https://www.postgresql.org/docs/current/static/textsearch-indexes.html*). You can add a GIN index using `CREATE INDEX` in Listing 13-20:

```
CREATE INDEX search_idx ON president_speeches USING gin(search_speech_text);
```

Listing 13-20: Creating a GIN index for text search

The GIN index contains an entry for each lexeme and its location, allowing the database to find matches more quickly.

NOTE *Another way to set up a column for search is to create an index on a text column using the* `to_tsvector()` *function. See* https://www.postgresql.org/docs/current/static/textsearch-tables.html *for details.*

Now you're ready to use search functions.

Searching Speech Text

Thirty-two years' worth of presidential speeches is fertile ground for exploring history. For example, the query in Listing 13-21 lists the speeches in which the president mentioned Vietnam:

```
SELECT president, speech_date
FROM president_speeches
```

```
❶ WHERE search_speech_text @@ to_tsquery('Vietnam')
  ORDER BY speech_date;
```

Listing 13-21: Finding speeches containing the word "Vietnam"

In the `WHERE` clause, the query uses the double-at sign (`@@`) match operator ❶ between the `search_speech_text` column (of data type `tsvector`) and the query term "Vietnam," which `to_tsquery()` transforms into `tsquery` data. The results should list 10 speeches, showing that the first mention of Vietnam came up in a 1961 special message to congress by John F. Kennedy and became a recurring topic starting in 1966 as America's involvement in the Vietnam War escalated.

```
    president         speech_date
-----------------    -----------
John F. Kennedy      1961-05-25
Lyndon B. Johnson    1966-01-12
Lyndon B. Johnson    1967-01-10
Lyndon B. Johnson    1968-01-17
Lyndon B. Johnson    1969-01-14
Richard M. Nixon     1970-01-22
Richard M. Nixon     1972-01-20
Richard M. Nixon     1973-02-02
Gerald R. Ford       1975-01-15
Gerald R. Ford       1977-01-12
```

Before we try more searches, let's add a method for showing the location of our search term in the text.

Showing Search Result Locations

To see where our search terms appear in text, we can use the `ts_headline()` function. It displays one or more highlighted search terms surrounded by adjacent words. Options for this function give you flexibility in how to format the display. Listing 13-22 highlights how to display a search for a specific instance of "Vietnam" using `ts_headline()`:

```
  SELECT president,
         speech_date,
❶        ts_headline(speech_text, to_tsquery('Vietnam'),
❷                    'StartSel = <,
                     StopSel = >,
                     MinWords=5,
                     MaxWords=7,
                     MaxFragments=1')
  FROM president_speeches
❸ WHERE search_speech_text @@ to_tsquery('Vietnam');
```

Listing 13-22: Displaying search results with `ts_headline()`

To declare `ts_headline()` ❶, we pass the original `speech_text` column rather than the `tsvector` column we used in the search and relevance functions as the first argument. Then, as the second argument, we pass a `to_tsquery()` function that specifies the word to highlight. We follow this with a third argument that lists optional formatting options ❷ separated by commas. Here, we specify the characters to identify the start and end of the highlighted word (`StartSel` and `StopSel`). We also set the minimum and maximum number of words to display (`MinWords` and `MaxWords`), plus the maximum number of fragments to show using `MaxFragments`. These settings are optional, and you can adjust them according to your needs.

The results of this query should show at most seven words per speech, highlighting the word "Vietnam":

```
    president        speech_date    ts_headline
-----------------    -----------    ------------------------------------------------
John F. Kennedy      1961-05-25     twelve months in <Vietnam> alone--by subversives
Lyndon B. Johnson    1966-01-12     bitter conflict in <Vietnam>. Later
Lyndon B. Johnson    1967-01-10     <Vietnam>--is not a simple one. There
Lyndon B. Johnson    1968-01-17     been held in <Vietnam>--in the midst
Lyndon B. Johnson    1969-01-14     conflict in <Vietnam>, the dangers of nuclear
Richard M. Nixon     1970-01-22     <Vietnam> in a way that our generation
--snip--
```

Using this technique, we can quickly see the context of the term we searched. You might also use this function to provide flexible display options for a search feature on a web application. Let's continue trying forms of searches.

Using Multiple Search Terms

As another example, we could look for speeches in which a president mentioned the word "transportation" but didn't discuss "roads." We might want to do this to find speeches that focused on broader policy rather than a specific roads program. To do this, we use the syntax in Listing 13-23:

```
SELECT president,
       speech_date,
❶      ts_headline(speech_text, to_tsquery('transportation & !roads'),
                    'StartSel = <,
                     StopSel = >,
                     MinWords=5,
                     MaxWords=7,
                     MaxFragments=1')
FROM president_speeches
❷ WHERE search_speech_text @@ to_tsquery('transportation & !roads');
```

Listing 13-23: Finding speeches with the word "transportation" but not "roads"

Again, we use `ts_headline()` ❶ to highlight the terms our search finds. In the `to_tsquery()` function in the `WHERE` clause ❷, we pass `transportation` and `roads`, combining them with the ampersand (`&`) operator. We use the exclamation point (!) in front of roads to indicate that we want speeches that do not contain this word. This query should find eight speeches that fit the criteria. Here are the first four rows:

```
president           speech_date   ts_headline
-----------------   -----------   ----------------------------------------------------------
Harry S. Truman     1947-01-06    such industries as <transportation>, coal, oil, steel
Harry S. Truman     1949-01-05    field of <transportation>.
John F. Kennedy     1961-01-30    Obtaining additional air <transport> mobility--and obtaining
Lyndon B. Johnson   1964-01-08    reformed our tangled <transportation> and transit policies
--snip--
```

Notice that the highlighted words in the ts_headline column include transportation and transport. The reason is that the to_tsquery() function converted transportation to the lexeme transport for the search term. This database behavior is extremely useful in helping to find relevant related words.

Searching for Adjacent Words

Finally, we'll use the distance (<->) operator, which consists of a hyphen between the less than and greater than signs, to find adjacent words. Alternatively, you can place a number between the signs to find terms that many words apart. For example, Listing 13-24 searches for any speeches that include the word "military" immediately followed by "defense":

```
SELECT president,
       speech_date,
       ts_headline(speech_text, to_tsquery('military <-> defense'),
                   'StartSel = <,
                    StopSel = >,
                    MinWords=5,
                    MaxWords=7,
                    MaxFragments=1')
FROM president_speeches
WHERE search_speech_text @@ to_tsquery('military <-> defense');
```

Listing 13-24: Finding speeches where "defense" follows "military"

This query should find four speeches, and because to_tsquery() converts the search terms to lexemes, the words identified in the speeches should include plurals, such as "military defenses." The following shows the four speeches that have the adjacent terms:

```
president              speech_date    ts_headline
--------------------   -----------    ---------------------------------------------------
Dwight D. Eisenhower   1956-01-05     system our <military> <defenses> are designed
Dwight D. Eisenhower   1958-01-09     direct <military> <defense> efforts, but likewise
Dwight D. Eisenhower   1959-01-09     survival--the <military> <defense> of national life
Richard M. Nixon       1972-01-20     spending. Strong <military> <defenses>
```

If you changed the query terms to `military <2> defense`, the database would return matches where the terms are exactly two words apart, as in the phrase "our military and defense commitments."

Ranking Query Matches by Relevance

You can also rank search results by relevance using two of PostgreSQL's full text search functions. These functions are helpful when you're trying to understand which piece of text, or speech in this case, is most relevant to your particular search terms.

One function, `ts_rank()`, generates a rank value (returned as a variable-precision `real` data type) based on how often the lexemes you're searching for appear in the text. The other function, `ts_rank_cd()`,considers how close the lexemes searched are to each other. Both functions can take optional arguments to take into account document length and other factors. The rank value they generate is an arbitrary decimal that's useful for sorting but doesn't have any inherent meaning. For example, a value of `0.375` generated during one query isn't directly comparable to the same value generated during a different query.

As an example, Listing 13-25 uses `ts_rank()` to rank speeches containing all the words "war," "security," "threat," and "enemy":

```
SELECT president,
       speech_date,
❶     ts_rank(search_speech_text,
               to_tsquery('war & security & threat & enemy')) AS score
FROM president_speeches
❷ WHERE search_speech_text @@ to_tsquery('war & security & threat & enemy')
ORDER BY score DESC
LIMIT 5
```

Listing 13-25: Scoring relevance with ts_rank()

In this query, the `ts_rank()` function ❶ takes two arguments: the `search_speech_text` column and the output of a `to_tsquery()` function containing the search terms. The output of the function receives the alias `score`. In the `WHERE` clause ❷ we filter the results to only those speeches that contain the search terms specified. Then we order the results in `score` in descending order and return just five of the highest-ranking speeches. The results should be as follows:

```
president              speech_date    rank_score
--------------------   -----------    ----------
Harry S. Truman        1946-01-21       0.257522
Lyndon B. Johnson      1968-01-17       0.186296
Dwight D. Eisenhower   1957-01-10       0.140851
Harry S. Truman        1952-01-09      0.0982469
Richard M. Nixon       1972-01-20      0.0973585
```

Harry S. Truman's 1946 State of the Union message, just four months after the end of World War II, contains the words "war," "security," "threat," and "enemy" more often than the other speeches. However, it also happens to be the longest speech in the table (which you can determine by using `char_length()`, as you learned earlier in the chapter). The length of the speeches influences these rankings because `ts_rank()` factors in the number of matching terms in a given text. Lyndon B. Johnson's 1968 State of the Union address, delivered at the height of the Vietnam War, comes in second.

It would be ideal to compare frequencies between speeches of identical lengths to get a more accurate ranking, but this isn't always possible. However, we can factor in the length of each speech by adding a normalization code as a third parameter of the `ts_rank()` function, as shown in Listing 13-26:

```
SELECT president,
       speech_date,
       ts_rank(search_speech_text,
               to_tsquery('war & security & threat & enemy'), 2❶)::numeric
               AS score
FROM president_speeches
WHERE search_speech_text @@ to_tsquery('war & security & threat & enemy')
ORDER BY score DESC
LIMIT 5;
```

Listing 13-26: Normalizing ts_rank() by speech length

Adding the optional code `2` ❶ instructs the function to divide the `score` by the length of the data in the `search_speech_text` column. This quotient then represents a score normalized by the document length, giving an apples-to-apples comparison among the speeches. The PostgreSQL documentation at *https://www.postgresql.org/docs/current/static/textsearch-controls.html* lists all the options available for text search, including using the document length and dividing by the number of unique words.

After running the code in Listing 13-26, the rankings should change:

```
president              speech_date    rank_score
--------------------   -----------    ------------
Lyndon B. Johnson      1968-01-17     0.0000728288
Dwight D. Eisenhower   1957-01-10     0.0000633609
Richard M. Nixon       1972-01-20     0.0000497998
Harry S. Truman        1952-01-09     0.0000365366
Dwight D. Eisenhower   1958-01-09     0.0000355315
```

In contrast to the ranking results in Listing 13-25, Johnson's 1968 speech now tops the rankings, and Truman's 1946 message falls out of the top five. This might be a more meaningful ranking than the first sample output, because we normalized it by length. But four of the five top-ranked speeches are the same between the two sets, and you can reasonably be certain that each of these four is worthy of closer examination to understand more about wartime presidential speeches.

Wrapping Up

Far from being boring, text offers abundant opportunities for data analysis. In this chapter, you've learned valuable techniques for turning ordinary text into data you can extract, quantify, search, and rank. In your work or studies, keep an eye out for routine reports that have facts buried inside chunks of text. You can use regular expressions to dig them out, turn them into structured data, and analyze them to find trends. You can also use search functions to analyze the text.

In the next chapter, you'll learn how PostgreSQL can help you analyze geographic information.

Try It Yourself

Use your new text-wrangling skills to tackle these tasks:

1. The style guide of a publishing company you're writing for wants you to avoid commas before suffixes in names. But your author database has several names like `Alvarez, Jr.` and `Williams, Sr.` Which functions can you use to remove the comma? Would a regular expression function help? How would you capture just the suffixes to place them into a separate column?
2. Using any one of the State of the Union addresses, count the number of unique words that are five characters or more. Hint: you can use `regexp_split_to_table()` in a subquery to create a table of words to count. Bonus: remove commas and periods at the end of each word.
3. Rewrite the query in Listing 13-25 using the `ts_rank_cd()` function instead of `ts_rank()`. According to the PostgreSQL documentation, `ts_rank_cd()` computes cover density, which takes into account how close the lexeme search terms are to each other. Does using the `ts_rank_cd()` function significantly change the results?

14

ANALYZING SPATIAL DATA WITH POSTGIS

These days, within seconds mobile apps can provide a list of coffee shops near you. They can do that because they're powered by a *geographic information system (GIS)*, which is any system that allows for storing, editing, analyzing, and displaying spatial data. As you can imagine, GIS has many practical applications today, from helping city planners decide where to build schools based on population patterns to finding the best detour around a traffic jam.

Spatial data refers to information about the location and shape of objects, which can be two and three dimensional. For example, the spatial data we'll use in this chapter contains coordinates describing geometric shapes, such as points, lines, and polygons. These shapes in turn represent features you would find on a map, such as roads, lakes, or countries.

Conveniently, you can use PostgreSQL to store and analyze spatial data, which allows you to calculate the distance between points, compute the size of areas, and identify whether two objects intersect. However, to enable spatial analysis and store spatial data types in PostgreSQL, you need to install an open source extension called PostGIS. The PostGIS extension also provides additional functions and operators that work specifically with spatial data.

In this chapter, you'll learn to use PostGIS to analyze roadways in Santa Fe, New Mexico as well as the location of farmer's markets across the United States. You'll learn how to construct and query spatial data types and how to work with different geographic data formats you might encounter when you obtain data from public and private data sources. You'll also learn about map projections and grid systems. The goal is to give you tools that help you glean information from spatial data, similar to how you've analyzed data from numbers and text.

We'll begin by setting up PostGIS so we can explore different types of spatial data. All code and data for the exercises are available with the book's resources at *https://www.nostarch.com/practicalSQL/*.

Installing PostGIS and Creating a Spatial Database

PostGIS is a free, open source project created by the Canadian geospatial company Refractions Research and maintained by an international team of developers under the Open Source Geospatial Foundation. You'll find documentation and updates at *http://postgis.net/*. If you're using Windows or macOS and have installed PostgreSQL following the steps in the book's Introduction, PostGIS should be on your machine. It's also often installed on PostgreSQL on cloud providers, such as Amazon Web Services. But if you're using Linux or if you installed PostgreSQL some other way on Windows or macOS, follow the installation instructions at *http://postgis.net/install/*.

Let's create a database and enable PostGIS. The process is similar to the one you used to create your first database in Chapter 1 but with a few extra steps. Follow these steps in pgAdmin to make a database called `gis_analysis`:

1. In the pgAdmin object browser (left pane), connect to your server and expand the **Databases** node by clicking the plus sign.
2. Click once on the `analysis` database you've used for past exercises.
3. Choose **Tools ▸ Query Tool**.
4. In the Query Tool, run the code in Listing 14-1.

```
CREATE DATABASE gis_analysis;
```

Listing 14-1: Creating a `gis_analysis` database

PostgreSQL will create the `gis_analysis` database, which is no different than others you've made. To enable PostGIS extensions on it, follow these steps:

1. Close the Query Tool tab.
2. In the object browser, right-click **Databases** and select **Refresh**.

3. Click the new `gis_analysis` database in the list to highlight it.
4. Open a new Query Tool tab by selecting **Tools ▸ Query Tool**. The `gis_analysis` database should be listed at the top of the editing pane.
5. In the Query Tool, run the code in Listing 14-2.

```
CREATE EXTENSION postgis;
```

Listing 14-2: Loading the PostGIS extension

You'll see the message `CREATE EXTENSION`. Your database has now been updated to include spatial data types and dozens of spatial analysis functions. Run **`SELECT postgis_full_version();`** to display the version number of PostGIS along with its installed components. The version won't match the PostgreSQL version installed, but that's okay.

The Building Blocks of Spatial Data

Before you learn to query spatial data, let's look at how it's described in GIS and related data formats (although if you want to dive straight into queries, you can skip to "Analyzing Farmers' Markets Data" on page xx and return here later).

A point on a grid is the smallest building block of spatial data. The grid might be marked with x- and y-axes, or longitude and latitude if we're using a map. A grid could be flat, with two dimensions, or it could describe a three-dimensional space such as a cube. In some data formats, such as the JavaScript-based *GeoJSON*, a point might have a location on the grid as well as attributes providing additional information. For example, a grocery store could be described by a point containing its longitude and latitude as well as attributes showing the store's name and hours of operation.

Two-Dimensional Geometries

To create more complex spatial data, you connect multiple points using lines. The International Organization for Standardization (ISO) and the Open Geospatial Consortium (OGC) have created a *simple feature* standard for building and accessing two- and three-dimensional shapes, sometimes referred to as *geometries*. PostGIS supports the standard.

The most commonly used simple features you'll encounter when querying or creating spatial data with PostGIS include the following:

Point A single location in a two- or three-dimensional plane. On maps, a Point is usually represented by a dot marking a longitude and latitude.

LineString Two or more points connected by a straight line. With multiple LineStrings, you can represent certain features, such as a road, hiking trail, or stream.

Polygon A two-dimensional shape that has three or more straight sides, each constructed from a LineString, like a triangle or a square. In geographic analysis, Polygons represent nations, states, buildings, and bodies of water. A Polygon also can have one or more interior Polygons that act as holes inside the larger Polygon.

MultiPoint A set of Points. For example, you can represent multiple locations of a retailer with a single MultiPoint object that contains each store's latitude and longitude.

MultiLineString A set of LineStrings that can represent a road with several noncontinuous segments.

MultiPolygon A set of Polygons. For example, you can represent a parcel of land that is divided into two parts by a road: you can group them in one MultiPolygon object rather than using separate polygons.

Figure 14-1 shows an example of each feature.

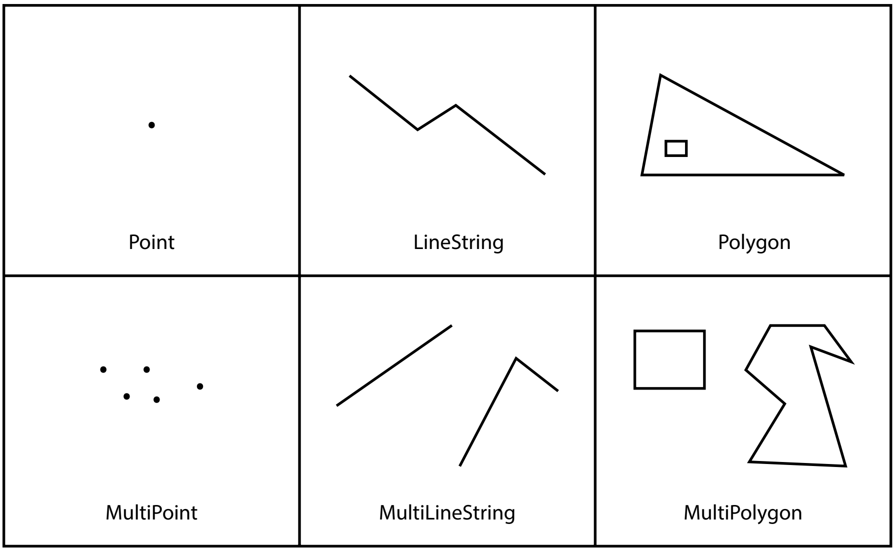


Figure 14-1: Visual examples of geometries

Using PostGIS functions, you can create your own spatial data by constructing these objects using points or other geometries. Or, you can use PostGIS functions to perform calculations on existing spatial data. Generally, to create a spatial object, the functions require input of a *well-known text (WKT)* string, which is text that represents a geometry, plus an optional *Spatial Reference System Identifier (SRID)* that specifies the grid on which to place the objects. I'll explain the SRID shortly, but first, let's look at examples of WKT strings and then build some geometries using them.

Well-Known Text Formats

The OGC standard's WKT format includes the geometry type and its coordinates inside one or more sets of parentheses. The number of coordinates and parentheses varies depending on the geometry you want to create. Table 14-1 shows examples of the more frequently used geometry types and their WKT formats. Here, I show longitude/latitude pairs for the coordinates, but you might encounter grid systems that use other measures.

NOTE *WKT accepts coordinates in the order of longitude, latitude, which is backwards from Google Maps and some other software. Tom MacWright, formerly of the Mapbox software company, notes at* https://macwright.org/lonlat/ *that neither order is "right" and catalogs the "frustrating inconsistency" in which mapping-related code handles the order of coordinates.*

Table 14-1: Well-Known Text Formats for Geometries

Geometry	Format	Notes
Point	`POINT (-74.9 42.7)`	A coordinate pair marking a point at –74.9 longitude and 42.7 latitude.
LineString	`LINESTRING (-74.9 42.7, -75.1 42.7)`	A straight line with endpoints marked by two coordinate pairs.
Polygon	`POLYGON ((-74.9 42.7, -75.1 42.7, -75.1 42.6, -74.9 42.7))`	A triangle outlined by three different pairs of coordinates. Although listed twice, the first and last pair are the same coordinates where we close the shape.
MultiPoint	`MULTIPOINT (-74.9 42.7, -75.1 42.7)`	Two points, one for each pair of coordinates.
MultiLineString	`MULTILINESTRING ((-76.27 43.1, -76.06 43.08), (-76.2 43.3, -76.2 43.4, -76.4 43.1))`	Two LineStrings. The first has two points; the second has three.
MultiPolygon	`MULTIPOLYGON (((-74.92 42.7, -75.06 42.71, -75.07 42.64, -74.92 42.7), (-75.0 42.66, -75.0 42.64, -74.98 42.64, -74.98 42.66, -75.0 42.66)))`	Two polygons. The first is a triangle, and the second is a rectangle.

Although these examples create simple shapes, in practice, complex geometries could comprise thousands of coordinates.

A Note on Coordinate Systems

Representing the Earth's spherical surface on a two-dimensional map is not easy. Imagine peeling the outer layer of the Earth from the globe and trying to spread it on a table while keeping all pieces of the continents and oceans connected. Inevitably, some areas of the map would stretch. This is what occurs when cartographers create a map *projection* with its own *projected coordinate system* that flattens the Earth's round surface to a two-dimensional plane.

Some projections represent the entire world; others are specific to regions or purposes. For example, the *Mercator projection* is commonly used for navigation in apps, such as Google Maps. The math behind its transformation distorts land areas close to the North and South Poles, making them appear much larger than reality. The *Albers projection* is the one you would most likely see displayed on TV screens in the United States as votes are tallied on election night. It's also used by the US Census Bureau.

Projections are derived from *geographic coordinate systems*, which define the grid of latitude, longitude, and height of any point on the globe along with factors including the Earth's shape. Whenever you obtain geographic data, it's critical to know the coordinate systems it references to check whether your calculations are accurate. Often, the coordinate system or projection is named in user documentation.

Spatial Reference System Identifier

When using PostGIS (and many GIS applications), you need to specify the coordinate system you're using via its SRID. When you enabled the PostGIS extension at the beginning of this chapter, the process created the table `spatial_ref_sys`, which contains SRIDs as its primary key. The table also contains the column `srtext`, which includes a WKT representation of the spatial reference system as well as other metadata.

In this chapter, we'll frequently use SRID `4326`, the ID for the geographic coordinate system WGS 84. It's the most recent World Geodetic System (WGS) standard used by GPS, and you'll encounter it often if you acquire spatial data. You can see the WKT representation for WGS 84 by running the code in Listing 14-3 that looks for its SRID, `4326`:

```
SELECT srtext
FROM spatial_ref_sys
WHERE srid = 4326;
```

Listing 14-3: Retrieving the WKT for SRID `4326`

Run the query and you should get the following result, which I've indented for readability:

```
GEOGCS["WGS 84",
    DATUM["WGS_1984",
        SPHEROID["WGS 84",6378137,298.257223563,
            AUTHORITY["EPSG","7030"]],
        AUTHORITY["EPSG","6326"]],
    PRIMEM["Greenwich",0,
        AUTHORITY["EPSG","8901"]],
    UNIT["degree",0.0174532925199433,
        AUTHORITY["EPSG","9122"]],
    AUTHORITY["EPSG","4326"]]
```

You don't need to use this information for any of this chapter's exercises, but it's helpful to know some of the variables and how they define the projection. The `GEOGCS` keyword provides the geographic coordinate system in use. Keyword `PRIMEM` specifies the location of the *Prime Meridian*, or longitude 0. To see definitions of all the variables, check the reference at *http://docs.geotools.org/stable/javadocs/org/opengis/referencing/doc-files/WKT.html.*

Conversely, if you ever need to find the SRID associated with a coordinate system, you can query the `srtext` column in `spatial_ref_sys` to find it.

PostGIS Data Types

Installing PostGIS adds five data types to your database. The two data types we'll use in the exercises are `geography` and `geometry`. Both types can store spatial data, such as points, lines, polygons, SRIDs, and so on you just learned about, but they have important distinctions:

Geography A data type based on a sphere, using the round-earth coordinate system (longitude and latitude). All calculations occur on the globe, taking its curvature into account. That makes the math complicated and limits the number of functions available to work with the `geography` type. But because the Earth's curvature is factored in, calculations for distance are more precise; you should use the `geography` data type when handling data that spans large areas. Also, the results from calculations on the `geography` type will be expressed in meters.

Geometry A data type based on a plane, using the Euclidean coordinate system. Calculations occur on straight lines as opposed to along the curvature of a sphere, making calculations for geographical distance less precise than with the `geography` data type; the results of calculations are expressed in units of whichever coordinate system you've designated.

The PostGIS documentation at *https://postgis.net/docs/using_postgis_dbmanagement.html* offers guidance on when to use one or the other type. In short, if you're working strictly with longitude/latitude data or if your data covers a large area, such as a continent or the globe, use the `geography` type, even though it limits the functions you can use. If your data covers a smaller area, the `geometry` type provides more functions and better performance. You can also change one type to the other using `CAST`.

With the background you have now, we can start working with spatial objects.

Creating Spatial Objects with PostGIS Functions

PostGIS has more than three dozen constructor functions that build spatial objects using WKT or coordinates. You can find a list at *https://postgis.net/docs/reference.html#Geometry_Constructors*, but the following sections explain several that you'll use in the exercises. Most PostGIS functions begin with the letters ST, which is an ISO naming standard that means *spatial type*.

Creating a Geometry Type from Well-Known Text

The `ST_GeomFromText(`*`WKT, SRID`*`)` function creates a `geometry` data type from an input of a WKT string and an optional SRID. Listing 14-4 shows simple

SELECT statements that generate geometry data types for each of the simple features described in Table 14-1. Running these SELECT statements is optional, but it's important to know how to construct each simple feature.

```
SELECT ST_GeomFromText(❶'POINT(-74.9233606 42.699992)', ❷4326);

SELECT ST_GeomFromText('LINESTRING(-74.9 42.7, -75.1 42.7)', 4326);

SELECT ST_GeomFromText('POLYGON((-74.9 42.7, -75.1 42.7,
                                 -75.1 42.6, -74.9 42.7))', 4326);

SELECT ST_GeomFromText('MULTIPOINT (-74.9 42.7, -75.1 42.7)', 4326);

SELECT ST_GeomFromText('MULTILINESTRING((-76.27 43.1, -76.06 43.08),
                                        (-76.2 43.3, -76.2 43.4,
                                         -76.4 43.1))', 4326);

SELECT ST_GeomFromText('MULTIPOLYGON❸((
                                       (-74.92 42.7, -75.06 42.71,
                                        -75.07 42.64, -74.92 42.7)❹,
                                       (-75.0 42.66, -75.0 42.64,
                                        -74.98 42.64, -74.98 42.66,
                                        -75.0 42.66)))', 4326);
```

Listing 14-4: Using `ST_GeomFromText()` *to create spatial objects*

For each example, we give coordinates as the first input and the SRID 4326 as the second. In the first example, we create a point by inserting the WKT POINT string ❶ as the first argument to ST_GeomFromText() with the SRID ❷ as the optional second argument. We use the same format in the rest of the examples. Note that we don't have to indent the coordinates. I only do so here to make the coordinate pairs more readable.

Be sure to keep track of the number of parentheses that segregate objects, particularly in complex structures, such as the MultiPolygon. For example, we need to use two opening parentheses ❸ and enclose each polygon's coordinates within another set of parentheses ❹.

Executing each statement should return the geometry data type encoded in a string of characters that looks something like this truncated example:

```
0101000020E61000008EDA0E5718BB52C017BB7D5699594540 ...
```

This result shows how the data is stored in a table. Typically, you won't be reading that string of code. Instead, you'll use geometry (or geography) columns as inputs to functions.

Creating a Geography Type from Well-Known Text

To create a geography data type, you can use ST_GeogFromText(*WKT* or *EWKT*) to convert a WKT or a PostGIS-specific variation called *extended WKT* that includes the SRID to a geography data type. Listing 14-5 shows how to pass in the SRID as part of the extended WKT string to create a MultiPoint geography object with three points:

```
SELECT
ST_GeogFromText('SRID=4326;MULTIPOINT(-74.9 42.7, -75.1 42.7, -74.924 42.6)')
```

Listing 14-5: Using `ST_GeogFromText()` to create spatial objects

Along with the all-purpose functions `ST_GeomFromText()` and `ST_GeogFromText()`, PostGIS includes several that are specific to creating certain spatial objects. I'll cover those briefly next.

Point Functions

The `ST_PointFromText()` and `ST_MakePoint()` functions will turn a WKT `POINT` into a `geometry` data type. Points mark coordinates, such as longitude and latitude, which you would use to identify locations or use as building blocks of other objects, such as LineStrings.

Listing 14-6 shows how these functions work:

```
SELECT ❶ST_PointFromText('POINT(-74.9233606 42.699992)', 4326);

SELECT ❷ST_MakePoint(-74.9233606, 42.699992);
SELECT ❸ST_SetSRID(ST_MakePoint(-74.9233606, 42.699992), 4326);
```

Listing 14-6: Functions specific to making points

The `ST_PointFromText(WKT, SRID)` ❶ function creates a point `geometry` type from a WKT `POINT` and an optional SRID as the second input. The PostGIS docs note that the function includes validation of coordinates that makes it slower than the `ST_GeomFromText()` function.

The `ST_MakePoint(x, y, z, m)` ❷ function creates a point `geometry` type on a two-, three-, and four-dimensional grid. The first two parameters, *x* and *y* in the example, represent longitude and latitude coordinates. You can use the optional *z* to represent altitude and *m* to represent a fourth-dimensional measure, such as time. That would allow you to mark a location at a certain time, for example. The `ST_MakePoint()` function is faster than `ST_GeomFromText()` and `ST_PointFromText()`, but if you want to specify an SRID, you'll need to designate one by wrapping it inside the `ST_SetSRID()` ❸ function.

LineString Functions

Now let's examine some functions we use specifically for creating LineString `geometry` data types. Listing 14-7 shows how they work:

```
SELECT ❶ST_LineFromText('LINESTRING(-105.90 35.67,-105.91 35.67)', 4326);
SELECT ❷ST_MakeLine(ST_MakePoint(-74.9, 42.7), ST_MakePoint(-74.1, 42.4));
```

Listing 14-7: Functions specific to making LineStrings

The `ST_LineFromText(WKT, SRID)` ❶ function creates a LineString from a WKT `LINESTRING` and an optional SRID as its second input. Like `ST_PointFromText` earlier, this function includes validation of coordinates that makes it slower than `ST_GeomFromText()`.

The `ST_MakeLine(geom, geom)` ❷ function creates a LineString from inputs that must be of the `geometry` data type. In Listing 14-7, the example uses two `ST_MakePoint()` functions as inputs to create the start and endpoint of the line. You can also pass in an `ARRAY` object with multiple points, perhaps generated by a subquery, to generate a more complex line.

Polygon Functions

Here, we'll look at three Polygon functions: `ST_PolygonFromText()`, `ST_MakePolygon()`, and `ST_MPolyFromText()`. All create `geometry` data types. Listing 14-8 shows how you can create Polygons with each:

```
SELECT ❶ST_PolygonFromText('POLYGON((-74.9 42.7, -75.1 42.7,
                                     -75.1 42.6, -74.9 42.7))', 4326);

SELECT ❷ST_MakePolygon(
           ST_GeomFromText('LINESTRING(-74.92 42.7, -75.06 42.71,
                                        -75.07 42.64, -74.92 42.7)', 4326));

SELECT ❸ST_MPolyFromText('MULTIPOLYGON((
                                        (-74.92 42.7, -75.06 42.71,
                                         -75.07 42.64, -74.92 42.7),
                                        (-75.0 42.66, -75.0 42.64,
                                         -74.98 42.64, -74.98 42.66,
                                         -75.0 42.66)
                                       ))', 4326);
```

Listing 14-8: Functions specific to making Polygons

The `ST_PolygonFromText(WKT, SRID)` ❶ function creates a Polygon from a WKT `POLYGON` and an optional SRID. As with the similarly named functions for creating points and lines, it includes a validation step that makes it slower than `ST_GeomFromText()`.

The `ST_MakePolygon(linestring)` ❷ function creates a Polygon from a LineString that must open and close with the same coordinates, ensuring the object is closed. This example uses `ST_GeomFromText()` to create the LineString geometry using a WKT `LINESTRING`.

The `ST_MPolyFromText(WKT, SRID)` ❸ function creates a MultiPolygon from WKT and an optional SRID.

Now you have the building blocks to analyze spatial data. Next, we'll use them to explore a set of data.

Analyzing Farmers' Markets Data

The National Farmers' Market Directory from the US Department of Agriculture catalogs the location and offerings of more than 8,600 "markets that feature two or more farm vendors selling agricultural products directly to customers at a common, recurrent physical location," according to *https://www.ams.usda.gov/local-food-directories/farmersmarkets/*. Attending these markets makes for an enjoyable weekend activity, so it would help to find those within a reasonable traveling distance. We can use SQL spatial queries to find the closest markets.

The *farmers_markets.csv* file contains a portion of the USDA data on each market, and it's available along with the book's resources at *https://www.nostarch.com/practicalSQL/*. Save the file to your computer and run the code in Listing 14-9 to create and load a `farmers_markets` table. Make sure you're connected to the `gis_analysis` database you made earlier in this chapter, and change the `COPY` statement file path to match your file's location.

```
CREATE TABLE farmers_markets (
    fmid bigint PRIMARY KEY,
    market_name varchar(100) NOT NULL,
    street varchar(180),
    city varchar(60),
    county varchar(25),
    st varchar(20) NOT NULL,
    zip varchar(10),
    longitude numeric(10,7),
    latitude numeric(10,7),
    organic varchar(1) NOT NULL
);

COPY farmers_markets
FROM 'C:\YourDirectory\farmers_markets.csv'
WITH (FORMAT CSV, HEADER);
```

Listing 14-9: Creating and loading the `farmers_markets` *table*

The table contains routine address data plus the `longitude` and `latitude` for most markets. Twenty-nine of the markets were missing those values when I downloaded the file from the USDA. An `organic` column indicates whether the market offers organic products; a hyphen (-) in that column indicates an unknown value. After you import the data, count the rows using `SELECT count(*) FROM farmers_markets;`, and if everything imported correctly, you should have 8,681 rows.

Creating and Filling a Geography Column

To perform spatial queries on the markets' longitude and latitude, we need to convert those coordinates into a single column of a spatial data type. Because we're working with locations spanning the entire United States and an accurate measurement of a large spherical distance is important, we'll use the geography type. After creating the column, we can update it using Points derived from the coordinates, and then apply an index to speed queries. Listing 14-10 contains the statements for doing these tasks:

```
❶ ALTER TABLE farmers_markets ADD COLUMN geog_point geography(POINT,4326);

UPDATE farmers_markets
SET geog_point =
    ❷ST_SetSRID(
              ❸ST_MakePoint(longitude,latitude),4326
              )❹::geography;

❺ CREATE INDEX market_pts_idx ON farmers_markets USING GIST (geog_point);

SELECT longitude,
       latitude,
       geog_point,
       ❻ST_AsText(geog_point)
FROM farmers_markets
WHERE longitude IS NOT NULL
LIMIT 5;
```

Listing 14-10: Creating and indexing a geography column

The ALTER TABLE statement ❶ you learned in Chapter 9 with the ADD COLUMN option creates a column of the geography type called geog_point that will hold points and reference the WSG 84 coordinate system, which we denote using SRID 4326.

Next, we run a standard UPDATE statement to fill the geog_point column. Nested inside a ST_SetSRID() ❷ function, the ST_MakePoint() ❸ function takes as input the longitude and latitude columns from the table. The output, which is the geometry type by default, must be cast to geography to match the geog_point column type. To do this, we use the PostgreSQL-specific double-colon syntax (::) ❹ for casting data types.

Adding a GiST Index

Before you start analysis, it's wise to add an index to the new column to speed up calculations. In Chapter 7, you learned about PostgreSQL's default index, the *B-Tree*. A B-Tree index is useful for data that you can order and search using equality and range operators, but it's less useful for spatial objects. The reason is that you cannot easily sort GIS data along one axis. For example, the application has no way to determine which of these coordinate pairs is greatest: (0,0), (0,1), or (1,0).

Instead, for spatial data, the makers of PostGIS recommend using the Generalized Search Tree (GiST) index. PostgreSQL core team member Bruce Momjian describes GiST as "a general indexing framework designed to allow indexing of complex data types," including geometries.

The CREATE INDEX statement ❺ in Listing 14-10 adds a GiST index to geog_point. We can then use the SELECT statement to view the geography data to show the newly encoded `geog_points` column. To view the WKT version of `geog_point`, we wrap it in a `ST_AsText()` function ❻. The first five rows should look like this, with `geog_point` truncated for brevity:

```
longitude       latitude      geog_point       st_astext
------------    ----------    -------------    ----------------------------
-121.9982460    37.5253970    010100002 ...    POINT(-121.998246 37.525397)
-100.5288290    39.8204690    010100002 ...    POINT(-100.528829 39.820469)
 -92.6256000    44.8560000    010100002 ...    POINT(-92.6256 44.856)
-104.8997430    39.7580430    010100002 ...    POINT(-104.899743 39.758043)
-101.9175330    33.5480160    010100002 ...    POINT(-101.917533 33.548016)
```

Now we're ready to perform calculations on the points.

Finding Geographies Within a Distance

While in Iowa in 2014 to report a story on farming, I visited the massive Downtown Farmers' Market in Des Moines. With hundreds of vendors, the market spans several city blocks in the Iowa capital. Farming is big business in Iowa, and even though the downtown market is huge, it's not the only one in the area. Let's use PostGIS to find more farmers' markets within a short distance from the downtown Des Moines market.

The PostGIS function `ST_DWithin()` returns a Boolean value of `true` if one spatial object is within a specified distance of another object. If you're working with the geography data type, as we are here, you need to use meters as the distance unit. If you're using the geometry type, use the distance unit specified by the SRID.

NOTE *PostGIS distance measurements are on a straight line for geometry data, whereas for geography data, they're on a sphere. Be careful not to confuse either with driving distance along roadways, which is usually farther from point to point. To perform calculations related to driving distances, check out the extension pgRouting at* http://pgrouting.org/.

Listing 14-11 uses the `ST_DWithin()` function to filter `farmers_markets` to show markets within 10 kilometers of the Downtown Farmers' Market in Des Moines:

```
SELECT market_name,
       city,
       st
FROM farmers_markets
WHERE ST_DWithin(❶geog_point,
                 ❷ST_GeogFromText('POINT(-93.6204386 41.5853202)'),
                  10000)
ORDER BY market_name;
```

Listing 14-11: Using `ST_DWithin()` to locate farmers' markets within 10 kilometers of a point

The first input for `ST_DWithin()` is `geog_point` ❶, which holds the location of each row's market in the `geography` data type. The second input is the

ST_GeogFromText() function ❷ that returns a point geography from WKT. The coordinates -93.6204386 and 41.5853202 represent the longitude and latitude of the Downtown Farmers' Market in Des Moines. The final input is 10000, which is the number of meters in 10 kilometers. The database calculates the distance between each market in the table and the downtown market. If a market is within 10 kilometers, it is included in the results.

We're using points here, but this function works with any geography or geometry type. If you're working with objects such as polygons, you can use the related ST_DFullyWithin() function to find objects that are completely within a specified distance.

Run the query; it should return nine rows:

```
market_name                               city               st
--------------------------------------    ---------------    ----
Beaverdale Farmers Market                 Des Moines         Iowa
Capitol Hill Farmers Market               Des Moines         Iowa
Downtown Farmers' Market - Des Moines     Des Moines         Iowa
Drake Neighborhood Farmers Market         Des Moines         Iowa
Eastside Farmers Market                   Des Moines         Iowa
Highland Park Farmers Market              Des Moines         Iowa
Historic Valley Junction Farmers Market   West Des Moines    Iowa
LSI Global Greens Farmers' Market         Des Moines         Iowa
Valley Junction Farmers Market            West Des Moines    Iowa
```

One of these nine markets is the Downtown Farmers' Market in Des Moines, which makes sense because its location is at the point used for comparison. The rest are other markets in Des Moines or in nearby West Des Moines. This operation should be familiar because it's a standard feature on many online maps and product apps that let you locate stores or points of interest near you.

Although this list of nearby markets is helpful, it would be even more helpful to know the exact distance of markets from downtown. We'll use another function to report that.

Finding Distance Between Geographies

The ST_Distance() function returns the minimum distance between two spatial objects. It also returns meters for geographies and SRID units for geometries. For example, Listing 14-12 calculates the distance in miles from Yankee Stadium in New York City's Bronx borough to Citi Field in Queens, home of the New York Mets:

```
SELECT ST_Distance(
                   ST_GeogFromText('POINT(-73.9283685 40.8296466)'),
                   ST_GeogFromText('POINT(-73.8480153 40.7570917)')
                   ) / 1609.344 AS mets_to_yanks;
```

Listing 14-12: Using ST_Distance() to calculate the miles between Yankee Stadium and Citi Field (Mets)

In this example, to see the result in miles, we divide the result of the `ST_Distance()` function by `1609.344` (the number of meters in a mile) to convert the unit of distance from meters to miles. The result is about 6.5 miles:

```
mets_to_yanks
----------------
6.54386182787521
```

Let's apply this technique for finding distance between points to the farmers' market data using the code in Listing 14-13. We'll display all farmers' markets within five miles of the Downtown Farmers' Market in Des Moines and show the distance in miles:

```
SELECT market_name,
       city,
      ❶round(
            (ST_Distance(geog_point,
                         ST_GeogFromText('POINT(-93.6204386 41.5853202)')
                         ) / 1609.344)❷::numeric(8,5), 2
            ) AS miles_from_dt
FROM farmers_markets
❸ WHERE ST_DWithin(geog_point,
                 ST_GeogFromText('POINT(-93.6204386 41.5853202)'),
                 10000)
ORDER BY miles_from_dt ASC;
```

Listing 14-13: Using `ST_Distance()` for each row in `farmers_markets`

The query is similar to Listing 14-11, which used `ST_DWithin()` to find markets 10 kilometers or closer to downtown, but adds the `ST_Distance()` function as a column to calculate and display the distance from downtown. I've wrapped the function inside `round()` ❶ to trim the output.

We provide `ST_Distance()` with the same two inputs we gave `ST_DWithin()` in Listing 14-11: `geog_point` and the `ST_GeogFromText()` function. The `ST_Distance()` function then calculates the distance between the points specified by both inputs, returning the result in meters. To convert to miles, we divide by `1609.344` ❷, which is the approximate number of meters in a mile. Then, to provide the `round()` function with the correct input data type, we cast the column result to type `numeric`.

The `WHERE` clause ❸ uses the same `ST_DWithin()` function and inputs as in Listing 14-11. You should see the following results, ordered by distance in ascending order:

```
market_name                            city             miles_from_dt
-------------------------------------  ---------------  -------------
Downtown Farmers' Market - Des Moines  Des Moines                0.00
Capitol Hill Farmers Market            Des Moines                1.15
Drake Neighborhood Farmers Market      Des Moines                1.70
LSI Global Greens Farmers' Market      Des Moines                2.30
Highland Park Farmers Market           Des Moines                2.93
```

```
Eastside Farmers Market                  Des Moines              3.40
Beaverdale Farmers Market                Des Moines              3.74
Historic Valley Junction Farmers Market  West Des Moines         4.68
Valley Junction Farmers Market           West Des Moines         4.70
```

Again, this is the type of list you see every day on your phone or computer when you're searching online for a nearby store or address. You might also find it helpful for many other analysis scenarios, such as finding all the schools within a certain distance of a known source of pollution or all the houses within five miles of an airport.

NOTE *Another type of distance measurement supported by PostGIS,* K-Nearest Neighbor, *provides the ability to quickly find the closest point or shape to one you specify. For a lengthy overview of how it works, see* http://workshops.boundlessgeo.com/postgis-intro/knn.html.

So far, you've learned how to build spatial objects from WKT. Next, I'll show you a common data format used in GIS called the *shapefile* and how to bring it into PostGIS for analysis.

Working with Census Shapefiles

A *shapefile* is a GIS data format developed by Esri, a US company known for its ArcGIS mapping visualization and analysis platform. In addition to serving as the standard file format for GIS platforms—such as ArcGIS and the open source QGIS—governments, corporations, nonprofits, and technical organizations use shapefiles to display, analyze, and distribute data that includes a variety of geographic features, such as buildings, roads, and territorial boundaries.

Shapefiles contain the information describing the shape of a feature (such as a county, a road, or a lake) as well as a database containing attributes about them. Those attributes might include their name and other descriptors. When you load a shapefile into a GIS platform that supports visualization, you can view the shapes and query their attributes. PostgreSQL, with the PostGIS extension, doesn't visualize the shapefile data, but it does allow you to run complex queries on the spatial data in the shapefile, which we'll do in "Exploring the Census 2010 Counties Shapefile" on page 259 and "Performing Spatial Joins" on page 262.

First, let's examine the structure and contents of shapefiles.

Contents of a Shapefile

A shapefile refers to a collection of files with different extensions, and each serves a different purpose. Usually, when you download a shapefile from a source, it comes in a compressed archive, such as *.zip*. You'll need to unzip it to access the individual files.

Per ArcGIS documentation, these are the most common extensions you'll encounter:

.shp Main file that stores the feature geometry.

.shx Index file that stores the index of the feature geometry.

.dbf Database table (in dBASE format) that stores the attribute information of features.

.xml XML-format file that stores metadata about the shapefile.

.prj Projection file that stores the coordinate system information. You can open this file with a text editor to view the geographic coordinate system and projection.

According to the documentation, files with the first three extensions include necessary data required for working with a shapefile. The other file types are optional. You can load a shapefile into PostGIS to access its spatial objects and the attributes for each. Let's do that next and explore some additional analysis functions.

Loading Shapefiles via the GUI Tool

There are two ways to load shapefiles into your database. The PostGIS suite includes a Shapefile Import/Export Manager with a simple graphical user interface (GUI), which users may prefer. Alternately, you can use the command-line application `shp2pgsql`, which is described in "Loading Shapefiles via the Command Line" on page XX.

Let's start with a look at how to work with the GUI tool.

Windows Shapefile Importer/Exporter

On Windows, if you followed the installation steps in the book's Introduction, you should find the Shapefile Import/Export Manager by selecting **Start ▸ PostGIS Bundle *x.y* for PostgreSQL x64 *x.y* ▸ PostGIS 2.0 Shapefile and DBF Loader Exporter**.

Whatever you see in place of *x.y* should match the version of the software you downloaded. You can skip ahead to the section "Connecting to the Database and Loading a Shapefile."

macOS and Linux Shapefile Importer/Exporter

On macOS, the *postgres.app* installation outlined in the book's Introduction doesn't include the GUI tool, and as of this writing the only macOS version of the tool available (from the geospatial firm Boundless) doesn't work with macOS High Sierra. I'll update the status at the book's resources at *https://www.nostarch.com/practicalSQL/* if that changes. In the meantime, follow the instructions found in "Loading Shapefiles via the Command Line" on page XX.

For Linux users, pgShapeLoader is available as the application *shp2pgsql-gui*. Visit *http://postgis.net/install/* and follow the instructions for your Linux distribution.

Now, you can connect to the database and load a shapefile.

Connecting to the Database and Loading a Shapefile

Let's connect the Shapefile Import/Export Manager to your database and then load a shapefile. I've included several shapefiles with the resources for this chapter at *https://www.nostarch.com/practicalSQL/*. We'll start with TIGER/Line Shapefiles from the US Census that contain the boundaries for each county or county equivalent, such as parish or borough, as of the 2010 Decennial Census. You can learn more about this series of shapefiles at *https://www.census.gov/geo/maps-data/data/tiger-line.html*.

NOTE *Many organizations provide data in shapefile format. Start with your national or local government agencies or check the Wikipedia entry "List of GIS data sources."*

Save *tl_2010_us_county10.zip* to your computer and unzip it; the archive should contain five files with the extensions I listed earlier in "Contents of a Shapefile" on page 256. Then open the Shapefile and DBF Loader Exporter app.

First, you need to establish a connection between the app and your `gis_analysis` database. To do that, follow these steps:

1. Click **View connection details**.
2. In the dialog that opens, enter `postgres` for the **Username**, and enter a password if you added one for the server during initial setup.
3. Ensure that **Server host** has `localhost` and `5432` by default. Leave those as is unless you're on a different server or port.
4. Enter `gis_analysis` for the **Database** name.

   Figure 14-2 shows a screenshot of what the connection should look like.

5. Click **OK**. You should see the message `Connection Succeeded` in the log window.

Now that you've successfully established the PostGIS connection, you can load your shapefile:

1. Under **Options**, change **DBF file character encoding** to `Latin1`—we do this because the shapefile attributes include county names with characters that require this encoding. Keep the default checked boxes, including the one to create an index on the spatial column. Click **OK**.

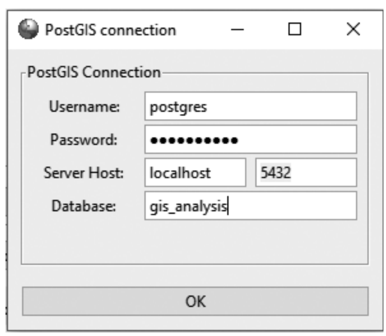


Figure 14-2: Establishing the PostGIS connection in the shapefile loader

2. Click **Add File** and select *tl_2010_us_county10.shp* from the location you saved it. Click **Open**. The file should appear in the Shapefile list in the loader, as shown in Figure 14-3.

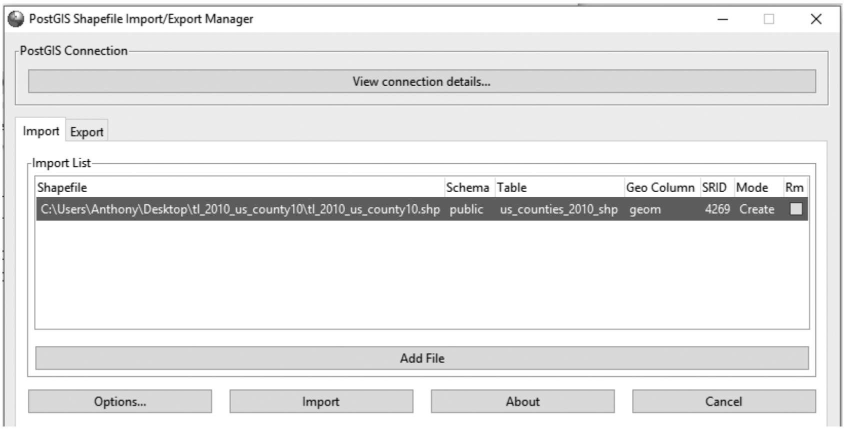


Figure 14-3: Specifying upload details in the shapefile loader

3. In the **Table** column, double-click to select the table name. Replace it with `us_counties_2010_shp`.
4. In the **SRID** column, double-click and enter `4269`. That's the ID for the North American Datum 1983 coordinate system, which is often used by US federal agencies including the Census Bureau.
5. Click **Import**.

In the log window, you should see a message that ends with the following message:

```
Shapefile type: Polygon
PostGIS type: MULTIPOLYGON[2]
Shapefile import completed.
```

Switch to pgAdmin, and in the object browser, expand the `gis_analysis` node and continue expanding by selecting **Schemas ▸ public ▸ Tables**. Refresh your tables by right-clicking **Tables** and selecting **Refresh** from the pop-up menu. You should see `us_counties_2010_shp` listed. Congrats! You've loaded your shapefile into a table. As part of the import, the shapefile loader also indexed the `geom` column.

Exploring the Census 2010 Counties Shapefile

The `us_counties_2010_shp` table contains columns including each county's name as well as the *Federal Information Processing Standards (FIPS)* codes uniquely assigned to each state and county. The `geom` column contains the spatial data on each county's boundary. To start, let's check what kind of spatial object geom contains using the ST_AsText() function. Use the code in Listing 14-14 to show the WKT representation of the first geom value in the table.

```
SELECT ST_AsText(geom)
FROM us_counties_2010_shp
LIMIT 1;
```

Listing 14-14: Checking the geom column's WKT representation

The result is a MultiPolygon with hundreds of coordinate pairs that outline the boundary of the county. Here's a portion of the output:

```
MULTIPOLYGON(((-162.637688 54.801121,-162.641178 54.795317,-162.644046
54.789099,-162.653751 54.780339,-162.666629 54.770215,-162.677799 54.762716,-
162.692356 54.758771,-162.70676 54.754987,-162.722965 54.753155,-162.740178
54.753102,-162.76206 54.757968,-162.783454 54.765285,-162.797004 54.772181,-
162.802591 54.775817,-162.807411 54.779871,-162.811898 54.786852, --snip-- )))
```

Each coordinate pair marks a point on the boundary of the county. Now, you're ready to analyze the data.

Finding the Largest Counties in Square Miles

The census data leads us to a natural question: which county has the largest area? To calculate the county area, Listing 14-15 uses the ST_Area() function, which returns the area of a Polygon or MultiPolygon object. If you're working with a geography data type, ST_Area() returns the result in square meters. With a geometry data type, the function returns the area in SRID units. Typically, the units are not useful for practical analysis, but you can cast the geometry data to geography to obtain square meters. That's what we'll do here. This is a more intensive calculation than others we've done so far, so if you're using an older computer, expect extra time for the query to complete.

```
SELECT name10,
       statefp10 AS st,
       round(
             ( ST_Area(❶geom::geography) / ❷2589988.110336 )::numeric, 2
            )  AS ❸square_miles
FROM us_counties_2010_shp
ORDER BY square_miles ❹DESC
LIMIT 5;
```

Listing 14-15: Finding the largest counties by area using ST_Area()

The geom column is data type geometry, so to find the area in square meters, we cast the geom column as a geography data type using the double-colon syntax ❶. Then, to get square miles, we divide the area by 2589988.110336, which is the number of square meters in a square mile ❷. To make the result easier to read, I've wrapped it in a round() function and named the resulting column `square_miles` ❸. Finally, we list the results in descending order from the largest area to the smallest ❹ and use `LIMIT 5` to show only the first five results, which should look like this:

```
name10            st    square_miles
----------------  --    ------------
Yukon-Koyukuk     02       147805.08
North Slope       02        94796.21
Bethel            02        45504.36
Northwest Arctic  02        40748.95
Valdez-Cordova    02        40340.08
```

The five counties with the largest areas are all in Alaska, denoted by the state FIPS code `02`. Yukon-Koyukuk, located in the heart of Alaska, is more than 147,800 square miles. Keep that information in mind for the "Try It Yourself" exercise at the end of the chapter.

Finding a County by Longitude and Latitude

If you've ever wondered how website ads seem to know where you live ("You won't believe what this Boston man did with his old shoes!"), it's thanks to *geolocation services* that use various means, such as your phone's GPS, to find your longitude and latitude. Once your coordinates are known, they can be used in a spatial query to find which geography contains that point.

You can do the same using your census shapefile and the `ST_Within()` function, which returns `true` if one geometry is inside another. Listing 14-16 shows an example using the longitude and latitude of downtown Hollywood:

```
SELECT name10,
       statefp10
FROM us_counties_2010_shp
WHERE ST_Within('SRID=4269;POINT(-118.3440306 34.0937851)'::geometry, geom);
```

Listing 14-16: Using `ST_Within()` to find the county belonging to a pair of coordinates

The `ST_Within()` function inside the `WHERE` clause requires two `geometry` inputs and checks whether the first is inside the second. For the function to work properly, both `geometry` inputs must have the same SRID. In this example, the first input is an extended WKT representation of a Point that includes the SRID `4269` (same as the census data), which is then cast as a `geometry` type. The `ST_Within()` function doesn't accept a separate SRID input, so to set it for the supplied WKT, you must prefix it to the string like this: `'SRID=4269;POINT(-118.3440306 34.0937851)'`. The second input is the `geom` column from the table. Run the query; you should see the following result:

```
name10       statefp10
-----------  ---------
Los Angeles  06
```

The query shows that the Point you supplied is within Los Angeles county in California (state FIPS `06`). This information is very handy, because by joining additional data to this table you can tell a person about demographics or points of interest near them. Try supplying other longitude and latitude pairs to see which US county they fall in. If you provide coordinates outside the United States, the query should return no results because the shapefile only contains US areas.

Performing Spatial Joins

In Chapter 6, you learned about SQL joins, which involved linking related tables via columns where values match or where an expression is true. You can perform joins using spatial data columns too, which opens up interesting opportunities for analysis. For example, you could join a table of coffee shops (which includes their longitude) to the counties table to find out how many shops exist in each county based on their location. Or, you can use a spatial join to append data from one table to another for analysis, again based on location. In this section, we'll explore spatial joins with a detailed look at roads and waterways using census data.

Exploring Roads and Waterways Data

Much of the year, the Santa Fe River, which cuts through the New Mexico state capital, is a dry riverbed better described as an *intermittent stream*. According to the Santa Fe city website, the river is prone to flooding and was named the nation's most endangered river in 2007. If you were an urban planner, it would help to know the locations where the river crosses roadways so you could plan for emergency response when it floods.

You can determine these locations using another set of US Census TIGER/Line shapefiles, which has details on roads and waterways in Santa Fe County. These shapefiles are also included with the book's resources. Download and unzip *tl_2016_35049_linearwater.zip* and *tl_2016_35049_roads.zip*, and then launch the Shapefile and DBF Loader Exporter. Following the same steps in "Loading Shapefiles via the GUI Tool" on page 257, import both shapefiles to `gis_analysis`. Name the water table `santafe_linearwater_2016` and the roads table `santafe_roads_2016`.

Next, refresh your database and run a quick `SELECT * FROM` query on both tables to view the data. You should have 12,926 rows in the roads table and 1,198 in the linear water table.

As with the counties shapefile you imported via the loader GUI, both tables have an indexed `geom` column of type `geometry`. It's helpful to check the type of spatial object in the column so you know the type of spatial feature you're querying. You can do that using the `ST_AsText()` function you learned in Listing 14-14 or using `ST_GeometryType()`, as shown in Listing 14-17:

```
SELECT ST_GeometryType(geom)
FROM santafe_linearwater_2016
LIMIT 1;

SELECT ST_GeometryType(geom)
```

```
FROM santafe_roads_2016
LIMIT 1;
```

Listing 14-17: Using `ST_GeometryType()` to determine geometry

Both queries should return one row with the same value: `ST_MultiLineString`. That value indicates that waterways and roads are stored as MultiLineString objects, which are a series of points connected by straight lines.

Joining the Census Roads and Water Tables

To find all the roads in Santa Fe that cross the Santa Fe River, we'll join the tables using the `JOIN ... ON` syntax you learned in Chapter 6. Rather than looking for values that match in columns in both tables as usual, we'll write a query that tells us where objects overlap. We'll do this using the `ST_Intersects()` function, which returns a Boolean `true` if two spatial objects contact each other. Inputs can be either `geometry` or `geography` types. Listing 14-18 joins the tables:

```
❶ SELECT water.fullname AS waterway,
         roads.rttyp,
         roads.fullname AS road
❷ FROM santafe_linearwater_2016 water JOIN santafe_roads_2016 roads
❸      ON ST_Intersects(water.geom, roads.geom)
  WHERE water.fullname = ❹'Santa Fe Riv'
  ORDER BY roads.fullname;
```

Listing 14-18: Spatial join with `ST_Intersects()` to find roads crossing the Santa Fe River

The `SELECT` column list ❶ includes the `fullname` column from the `santafe_linearwater_2016` table, which gets `water` as its alias in the `FROM` ❷ clause. The column list includes the `rttyp` code, which represents the route type, and `fullname` columns from the `santafe_roads_2016` table, aliased as `roads`.

In the `ON` portion ❸ of the `JOIN` clause, we use the `ST_Intersects()` function with the `geom` columns from both tables as inputs. This is an example of using the `ON` clause with an expression that evaluates to a Boolean result, as noted in "Linking Tables Using `JOIN`" on page 74. Then we use `fullname` to filter the results to show only those that have the full string `'Santa Fe Riv'` ❹, which is how the Santa Fe River is listed in the water table. The query should return 54 rows; here are the first five:

```
waterway        rttyp    road
------------    -----    ----------------
Santa Fe Riv    M        Baca Ranch Ln
Santa Fe Riv    M        Cam Alire
Santa Fe Riv    M        Cam Carlos Rael
Santa Fe Riv    M        Cam Dos Antonios
Santa Fe Riv    M        Cerro Gordo Rd
--snip--
```

Each road in the results intersects with a portion of the Santa Fe River. The route type code for each of the first results is `M`, which indicates that the road name shown is its *common* name as opposed to a county or state recognized name, for example. Other road names in the complete results carry route types of `C`, `S`, or `U` (for unknown). The full route type code list is available at *https://www.census.gov/geo/reference/rttyp.html*.

Finding the Location Where Objects Intersect

We successfully identified all the roads that intersect the Santa Fe River. This is a good start, but it would help our survey of flood-danger areas more to know precisely where each intersection occurs. We can modify the query to include the `ST_Intersection()` function, which returns the location of the place where objects cross. I've added it as a column in Listing 14-19:

```
SELECT water.fullname AS waterway,
       roads.rttyp,
       roads.fullname AS road,
       ❶ST_AsText(ST_Intersection(❷water.geom, roads.geom))
FROM santafe_linearwater_2016 water JOIN santafe_roads_2016 roads
    ON ST_Intersects(water.geom, roads.geom)
WHERE water.fullname = 'Santa Fe Riv'
ORDER BY roads.fullname;
```

Listing 14-19: Using `ST_Intersection()` to show where roads cross the river

The function returns a geometry object, so to get its WKT representation, we must wrap it in `ST_AsText()` ❶. The `ST_Intersection()` function takes two inputs: the `geom` columns ❷ from both the `water` and `roads` tables. Run the query, and the results should now include the exact coordinate location, or locations, where the river crosses the roads:

```
waterway       rttyp    road               st_astext
------------   -----    ----------------   ----------------------------
Santa Fe Riv   M        Baca Ranch Ln      POINT(-106.049782 35.642805)
Santa Fe Riv   M        Cam Alire          POINT(-105.967111 35.68479)
Santa Fe Riv   M        Cam Carlos Rael    POINT(-105.986712 35.672483)
Santa Fe Riv   M        Cam Dos Antonios   POINT(-106.007913 35.661576)
Santa Fe Riv   M        Cerro Gordo Rd     POINT(-105.895799 35.686198)
--snip--
```

You can probably think of more ideas for analyzing spatial data. For example, if you obtained a shapefile showing buildings, you could find those close to the river and in danger of flooding during heavy rains. Governments and private organizations regularly use these techniques as part of their planning process.

Wrapping Up

Mapping features is a powerful analysis tool, and the techniques you learned in this chapter provide you with a strong start toward exploring more with PostGIS. You might also want to look at the open source mapping application QGIS (*http://www.qgis.org/*), which provides tools for visualizing geographic data and working in depth with shapefiles. QGIS also works quite well with PostGIS, letting you add data from your tables directly onto a map.

You've now added working with geographic data to your analysis skills. In the remaining chapters, I'll give you additional tools and tips for working with PostgreSQL and related tools to continue to increase your skills.

Try It Yourself

Use the spatial data you've imported in this chapter to try additional analysis:

1. Earlier, you found which US county has the largest area. Now, aggregate the county data to find the area of each state in square miles. (Use the `statefp10` column in the `us_counties_2010_shp` table.) How many states are bigger than the Yukon-Koyukuk area?
2. Using `ST_Distance()`, determine how many miles separate these two farmers' markets: the Oakleaf Greenmarket (9700 Argyle Forest Blvd, Jacksonville, Florida) and Columbia Farmers Market (1701 West Ash Street, Columbia, Missouri). You'll need to first find the coordinates for both in the `farmers_markets` table. Tip: you can also write this query using the Common Table Expression syntax you learned in Chapter 12.
3. More than 500 rows in the `farmers_markets` table are missing a value in the `county` column, which is an example of dirty government data. Using the `us_counties_2010_shp` table and the `ST_Intersects()` function, perform a spatial join to find the missing county names based on the longitude and latitude of each market. Because `geog_point` in `farmers_markets` is of the `geography` type and its SRID is `4326`, you'll need to cast `geom` in the Census table to the `geography` type and change its SRID using `ST_SetSRID()`.