R, Databases and Docker

Dipti Muni, Ian Frantz, John David Smith, Mary Anne Thygesen, M. Edward (Ed) Borasky, Scott Case, and Sophie Yang

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Contents

Chapter 1

Introduction

At the end of this chapter, you will be able to

- Understand the importance of using R and Docker to query a DBMS and access a service like Postgres outside of R.
- Setup your environment to explore the use-case for useRs.

1.1 Using R to query a DBMS in your organization

1.1.1 Why write a book about DBMS access from R using Docker?

- Large data stores in organizations are stored in databases that have specific access constraints and structural characteristics.
  * Data documentation may be incomplete, often emphasizes operational issues rather than analytic ones, and often needs to be confirmed on the fly.
  * Data volumes and query performance are important design constraints.
- R users frequently need to make sense of complex data structures and coding schemes to address incompletely formed questions so that exploratory data analysis has to be fast. * Exploratory and diagnostic techniques for the purpose should not be reinvented and would benefit from more public instruction or discussion.
- Learning to navigate the interfaces (passwords, packages, etc.) or gap between R and a database is difficult to simulate outside corporate walls.
  * Resources for interface problem diagnosis behind corporate walls may or may not address all the issues that R users face, so a simulated environment is needed.
- Docker is a relatively easy way to simulate the relationship between an R/Rstudio session and database – all on a single machine.

1.2 Docker as a tool for UseRs

Noam Ross's "Docker for the UseR" suggests that there are four distinct Docker use-cases for useRs.

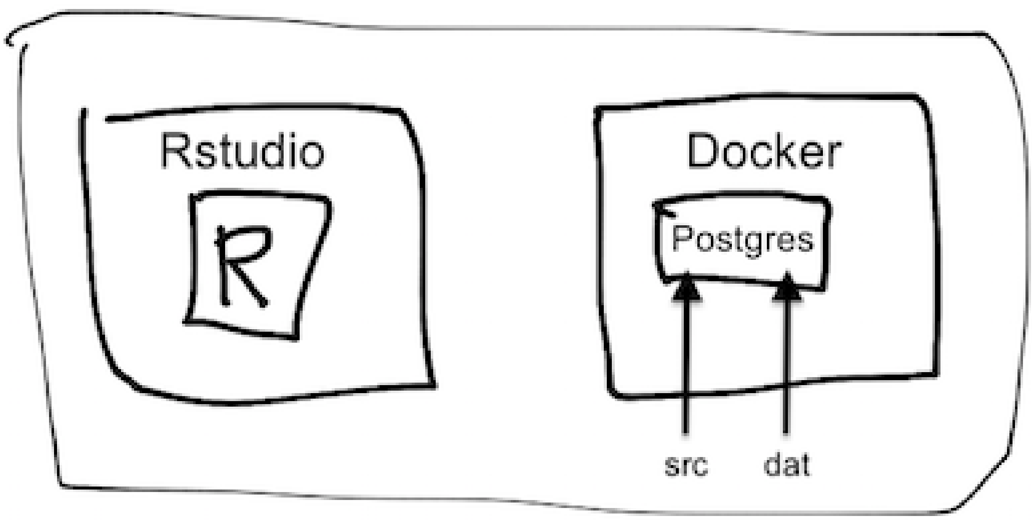
1. Make a fixed working environment for reproducible analysis
2. Access a service outside of R **(e.g., Postgres)**
3. Create an R based service (e.g., with `plumber`)
4. Send our compute jobs to the cloud with minimal reconfiguration or revision

This book explores #2 because it allows us to work on the database access issues described above and to practice on an industrial-scale DBMS.

- Docker is a relatively easy way to simulate the relationship between an R/RStudio session and a database – all on on a single machine, provided you have Docker installed and running.
- You may want to run PostgreSQL on a Docker container, avoiding any OS or system dependencies that might come up.

1.3 Docker and R on your machine

Here is how R and Docker fit on your operating system in this tutorial:



(This diagram needs to be updated as our directory structure evolves.)

1.4 Who are we?

We have been collaborating on this book since the Summer of 2018, each of us chipping into the project as time permits:

- Dipti Muni - @deemuni
- Ian Franz - @ianfrantz
- Jim Tyhurst - @jimtyhurst
- John David Smith - @smithjd
- M. Edward (Ed) Borasky - @znmeb
- Maryanne Thygesen @maryannet
- Scott Came - @scottcame
- Sophie Yang - @SophieMYang

Chapter 2

How to use this book (01)

This book is full of examples that you can replicate on your computer.

2.1 Prerequisites

You will need:

- A computer running
  - Windows (Windows 7 64-bit or late - Windows 10-Pro is recommended)
  - MacOS
  - Linux (any Linux distro that will run Docker Community Edition, R and RStudio will work)
- Current versions of R and RStudio required.
- Docker (instructions below)
- Our companion package `sqlpetr` installs with: `devtools::install_github("smithjd/sqlpetr")`.

The database we use is PostgreSQL 10, but you do not need to install it - it's installed via a Docker image.

In addition to the current version of R and RStudio, you will need current versions of the following packages:

- DBI
- DiagrammeR
- RPostgres
- dbplyr
- devtools
- downloader
- glue
- here
- knitr
- skimr
- tidyverse
- bookdown (for compiling the book, if you want to)

2.2 Installing Docker

Install Docker. Installation depends on your operating system:

- On a Mac
- On UNIX flavors
- For Windows, consider these issues and follow these instructions.

2.3 Download the repo

The code to generate the book and the exercises it contains can be downloaded from this repo.

2.4 Read along, experiment as you go

We have never been sure whether we're writing an expository book or a massive tutorial. You may use it either way.

After the introductory chapters and the chapter that creates the persistent database ("The dvdrental database in Postgres in Docker (05)), you can jump around and each chapter stands on its own.

Chapter 3

Docker Hosting for Windows (02)

At the end of this chapter, you will be able to

- Setup your environment for Windows.
- Use Git and GitHub effectively on Windows.

Skip these instructions if your computer has either OSX or a Unix variant.

3.1 Hardware requirements

You will need an Intel or AMD processor with 64-bit hardware and the hardware virtualization feature. Most machines you buy today will have that, but older ones may not. You will need to go into the BIOS / firmware and enable the virtualization feature. You will need at least 4 gigabytes of RAM!

3.2 Software requirements

You will need Windows 7 64-bit or later. If you can afford it, I highly recommend upgrading to Windows 10 Pro.

3.2.1 Windows 7, 8, 8.1 and Windows 10 Home (64 bit)

Install Docker Toolbox. The instructions are here: https://docs.docker.com/toolbox/toolbox_install_windows/. Make sure you try the test cases and they work!

3.2.2 Windows 10 Pro

Install Docker for Windows *stable*. The instructions are here: https://docs.docker.com/docker-for-windows/install/#start-docker-for-windows. Again, make sure you try the test cases and they work.

3.3 Additional technical details

See the Chapter on Additional technical details for Windows users (95) for more information.

Chapter 4

Learning Goals and Use Cases (03)

4.1 Learning Goals

After working through this tutorial, you can expect to be able to:

- Set up a PostgreSQL database in a Docker environment.
- Run queries against PostgreSQL in an environment that simulates what you will find in a corporate setting.
- Understand techniques and some of the trade-offs between:
    1. queries aimed at exploration or informal investigation using dplyr; and
    2. those where performance is important because of the size of the database or the frequency with which a query is run.
- Understand the equivalence between `dplyr` and SQL queries, and how R translates one into the other
- Understand some advanced SQL techniques.
- Gain familiarity with the standard metadata that a SQL database contains to describe its own contents.
- Gain some understanding of techniques for assessing query structure and performance.
- Understand enough about Docker to swap databases, e.g. Sports DB for the DVD rental database used in this tutorial. Or swap the database management system (DBMS), e.g. MySQL for PostgreSQL.

4.2 Managing a DVD rental business

- Years ago people rented videos on DVD disks, and video stores were a big business.
- Imagine managing a video rental store like Movie Madness in Portland, Oregon.

- What data would be needed and what questions would you have to answer about the business?

This tutorial uses the Postgres version of “dvd rental” database which represents the transaction database for running a movie (e.g., dvd) rental business. The database can be downloaded here. Here’s a glimpse of it’s structure, which will be discussed in some detail:

A data analyst uses the database abstraction and the practical business questions to make better decision and solve problems.

4.3 Use cases

Imagine that you have one of following several roles at our fictional company **DVDs R Us** and you have a following need to be met:

- As a data scientist, I want to know the distribution of number of rentals per month per customer, so that the Marketing department can create incentives for customers in 3 segments: Frequent Renters, Average Renters, Infrequent Renters.
- As the Director of Sales, I want to see the total number of rentals per month for the past 6 months and I want to know how fast our customer base is growing/shrinking per month for the past 6 months.
- As the Director of Marketing, I want to know which categories of DVDs are the least popular, so that I can create a campaign to draw attention to rarely used inventory.
- As a shipping clerk, I want to add rental information when I fulfill a shipment order.
- As the Director of Analytics, I want to test as much of the production R code in my shop as possible against a new release of the DBMS that the IT department is implementing next month.

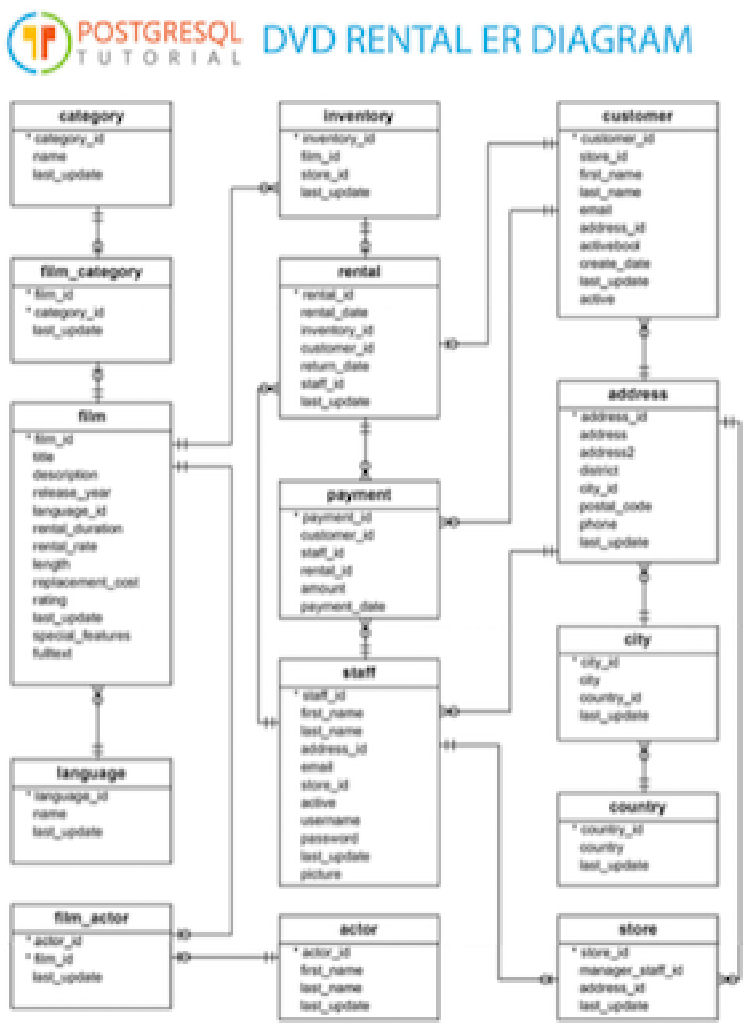


Figure 4.1: Entity Relationship diagram for the dvdrental database

- etc.

4.4 Investigating a question using with an organization's database

- Need both familiarity with the data and a focus question
  - An iterative process where
    * the data resource can shape your understanding of the question
    * the question you need to answer will frame how your see the data resource
  - You need to go back and forth between the two, asking
    * do I understand the question?
    * do I understand the data?
- How well do you understand the data resource (in the DBMS)?
  - Use all available documentation and understand its limits
  - Use your own tools and skills to examine the data resource
  - what's *missing* from the database: (columns, records, cells)
  - why is the missing data?
- How well do you understand the question you seek to answer?
  - How general or specific is your question?
  - How aligned is it with the purpose for which the database was designed and is being operated?
  - How different are your assumptions and concerns from those of the people who enter and use the data on a day to day basis?

Chapter 5

Docker, Postgres, and R (04)

At the end of this chapter, you will be able to

- Run, clean-up and close Docker containers.
- See how to keep credentials secret in code that's visible to the world.
- Interact with Postgres using Rstudio inside Docker container. # Read and write to postgreSQL from R.

We always load the tidyverse and some other packages, but don't show it unless we are using packages other than `tidyverse`, `DBI`, `RPostgres`, and `glue`.

Devtools install of sqlpetr if not already installed

5.1 Verify that Docker is running

Docker commands can be run from a terminal (e.g., the Rstudio Terminal pane) or with a `system()` command. In this tutorial, we use `system2()` so that all the output that is created externally is shown. Note that `system2` calls are divided into several parts:

1. The program that you are sending a command to.
2. The parameters or commands that are being sent.
3. `stdout = TRUE, stderr = TRUE` are two parameters that are standard in this book, so that the command's full output is shown in the book.

Check that docker is up and running:

```
sp_check_that_docker_is_up()
```

```
## [1] "Docker is up but running no containers"
```

5.2 Clean up if appropriate

Remove the `cattle` and `sql-pet` containers if they exists (e.g., from a prior experiments).

```
sp_docker_remove_container("cattle")
```

```
## Warning in system2("docker", docker_command, stdout = TRUE, stderr = TRUE):
## running command ''docker' rm -f cattle 2>&1' had status 1
```

```
## [1] "Error: No such container: cattle"
## attr(,"status")
```

```
## [1] 1
```

```
sp_docker_remove_container("sql-pet")
```

```
## [1] "sql-pet"
```

The convention we use in this book is to put docker commands in the `sqlpetr` package so that you can ignore them if you want. However, the functions are set up so that you can easily see how to do things with Docker and modify if you want.

We name containers `cattle` for "throw-aways" and `pet` for ones we treasure and keep around. :-)

```
sp_make_simple_pg("cattle")
```

```
## [1] 0
```

Docker returns a long string of numbers. If you are running this command for the first time, Docker downloads the PostgreSQL image, which takes a bit of time.

The following command shows that a container named `cattle` is running `postgres:10`. `postgres` is waiting for a connection:

```
sp_check_that_docker_is_up()
```

```
## [1] "Docker is up, running these containers:"
## [2] "CONTAINER ID      IMAGE           COMMAND                CREATED          STATUS               PORTS
## [3] "b24ba22910dc      postgres:10      \"docker-entrypoint.s…\"  1 second ago      Up Less than a second
```

5.3 Connect, read and write to Postgres from R

5.3.1 Pause for some security considerations

We use the following `sp_get_postgres_connection` function, which will repeatedly try to connect to PostgreSQL. PostgreSQL can take different amounts of time to come up and be ready to accept connections from R, depending on various factors that will be discussed later on.

This is how the `sp_get_postgres_connection` function is used:

```
con <- sp_get_postgres_connection(user = Sys.getenv("DEFAULT_POSTGRES_USER_NAME"),
                         password = Sys.getenv("DEFAULT_POSTGRES_PASSWORD"),
                         dbname = "postgres",
                         seconds_to_test = 10)
```

If you don't have an `.Rprofile` file that defines those passwords, you can just insert a string for the parameter, like:

`password = 'whatever',`

Make sure that you can connect to the PostgreSQL database that you started earlier. If you have been executing the code from this tutorial, the database will not contain any tables yet:

```
dbListTables(con)
```

```
## character(0)
```

5.3.2 Alternative: put the database password in an environment file

The goal is to put the password in an untracked file that will **not** be committed in your source code repository. Your code can reference the name of the variable, but the value of that variable will not appear in open text in your source code.

We have chosen to call the file `dev_environment.csv` in the current working directory where you are executing this script. That file name appears in the `.gitignore` file, so that you will not accidentally commit it. We are going to create that file now.

You will be prompted for the database password. By default, a PostgreSQL database defines a database user named `postgres`, whose password is `postgres`. If you have changed the password or created a new user with a different password, then enter those new values when prompted. Otherwise, enter `postgres` and `postgres` at the two prompts.

In an interactive environment, you could execute a snippet of code that prompts the user for their username and password with the following snippet (which isn't run in the book):

Your password is still in plain text in the file, `dev_environment.csv`, so you should protect that file from exposure. However, you do not need to worry about committing that file accidentally to your git repository, because the name of the file appears in the `.gitignore` file.

For security, we use values from the `environment_variables` data.frame, rather than keeping the `username` and `password` in plain text in a source file.

5.3.3 Interact with Postgres

Write `mtcars` to PostgreSQL

```
dbWriteTable(con, "mtcars", mtcars, overwrite = TRUE)
```

List the tables in the PostgreSQL database to show that `mtcars` is now there:

```
dbListTables(con)
```

```
## [1] "mtcars"
```

```
# list the fields in mtcars:
dbListFields(con, "mtcars")
```

```
##  [1] "mpg"  "cyl"  "disp" "hp"   "drat" "wt"   "qsec" "vs"   "am"   "gear"
## [11] "carb"
```

Download the table from the DBMS to a local data frame:

```
mtcars_df <- tbl(con, "mtcars")

# Show a few rows:
knitr::kable(head(mtcars_df))
```

mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
21.0	6	160	110	3.90	2.620	16.46	0	1	4	4
21.0	6	160	110	3.90	2.875	17.02	0	1	4	4
22.8	4	108	93	3.85	2.320	18.61	1	1	4	1
21.4	6	258	110	3.08	3.215	19.44	1	0	3	1
18.7	8	360	175	3.15	3.440	17.02	0	0	3	2
18.1	6	225	105	2.76	3.460	20.22	1	0	3	1

5.4 Clean up

Afterwards, always disconnect from the DBMS, stop the docker container and (optionally) remove it.

```
dbDisconnect(con)
```

```r
# tell Docker to stop the container:
sp_docker_stop("cattle")
```

```
## [1] "cattle"
```

```r
# Tell Docker to remove the container from it's library of active containers:
sp_docker_remove_container("cattle")
```

```
## [1] "cattle"
```

If we `stop` the docker container but don't remove it (with the `rm cattle` command), the container will persist and we can start it up again later with `start cattle`. In that case, `mtcars` would still be there and we could retrieve it from R again. Since we have now removed the `cattle` container, the whole database has been deleted. (There are enough copies of `mtcars` in the world, so no great loss.)

Chapter 6

The dvdrental database in Postgres in Docker (05)

At the end of this chapter, you will be able to

- Setup the `dvdrental` database
- Stop and start Docker container to demonstrate persistence
- Connect to and disconnect R from the `dvdrental` database
- Execute the code in subsequent chapters

6.1 Overview

In the last chapter we connected to PostgreSQL from R. Now we set up a "realistic" database named `dvdrental`. There are two different approaches to doing this: this chapter sets it up in a way that doesn't delve into the Docker details. If you are interested, you can examine the functions provided in `sqlpetr` to see how it works or look at an alternative approach in docker-detailed-postgres-setup-with-dvdrental.R)

Note that `tidyverse`, `DBI`, `RPostgres`, and `glue` are loaded.

6.2 Verify that Docker is up and running

```
sp_check_that_docker_is_up()
```

```
## [1] "Docker is up but running no containers"
```

6.3 Clean up if appropriate

Remove the `sql-pet` container if it exists (e.g., from a prior run)

```
sp_docker_remove_container("sql-pet")
```

```
## Warning in system2("docker", docker_command, stdout = TRUE, stderr = TRUE):
## running command ''docker' rm -f sql-pet 2>&1' had status 1

## [1] "Error: No such container: sql-pet"
## attr(,"status")
```

```
## [1] 1
```

6.4 Build the Docker Image

Build an image that derives from postgres:10, defined in `dvdrental.Dockerfile`, that is set up to restore and load the dvdrental db on startup. The dvdrental.Dockerfile is discussed below.

```
system2("docker",
        glue("build ", # tells Docker to build an image that can be loaded as a container
          "--tag postgres-dvdrental ", # (or -t) tells Docker to name the image
          "--file dvdrental.Dockerfile ", #(or -f) tells Docker to read `build` instructions from the d
          " . "),  # tells Docker to look for dvdrental.Dockerfile, and files it references, in the cur
          stdout = TRUE, stderr = TRUE)
```

```
##  [1] "Sending build context to Docker daemon  46.86MB\r\r"
##  [2] "Step 1/4 : FROM postgres:10"
##  [3] " ---> ac25c2bac3c4"
##  [4] "Step 2/4 : WORKDIR /tmp"
##  [5] " ---> Using cache"
##  [6] " ---> 3f00a18e0bdf"
##  [7] "Step 3/4 : COPY init-dvdrental.sh /docker-entrypoint-initdb.d/"
##  [8] " ---> Using cache"
##  [9] " ---> 3453d61d8e3e"
## [10] "Step 4/4 : RUN apt-get -qq update &&  apt-get install -y -qq curl zip  > /dev/null 2>&1 &&  curl -Os h
## [11] " ---> Using cache"
## [12] " ---> f5e93aa64875"
## [13] "Successfully built f5e93aa64875"
## [14] "Successfully tagged postgres-dvdrental:latest"
```

6.5 Run the Docker Image

Run docker to bring up postgres. The first time it runs it will take a minute to create the PostgreSQL environment. There are two important parts to this that may not be obvious:

- The `source=` parameter points to dvdrental.Dockerfile, which does most of the heavy lifting. It has detailed, line-by-line comments to explain what it is doing.

- *Inside* dvdrental.Dockerfile the command `COPY init-dvdrental.sh /docker-entrypoint-initdb.d/` copies init-dvdrental.sh from the local file system into the specified location in the Docker container. When the PostgreSQL Docker container initializes, it looks for that file and executes it.

Doing all of that work behind the scenes involves two layers of complexity. Depending on how you look at it, that may be more or less difficult to understand than the method shown in the next Chapter.

```
wd <- getwd()

docker_cmd <- glue(
  "run ",      # Run is the Docker command.  Everything that follows are `run` parameters.
  "--detach ", # (or `-d`) tells Docker to disconnect from the terminal / program issuing the command
  " --name sql-pet ",     # tells Docker to give the container a name: `sql-pet`
  "--publish 5432:5432 ", # tells Docker to expose the Postgres port 5432 to the local network with 543
  "--mount ", # tells Docker to mount a volume -- mapping Docker's internal file structure to the host f
  "type=bind,", # tells Docker that the mount command points to an actual file on the host system
  'source="', # specifies the directory on the host to mount into the container at the mount point spec
```

```
  wd, '",', # the current working directory, as retrieved above
  "target=/petdir", # tells Docker to refer to the current directory as "/petdir" in its file system
  " postgres-dvdrental" # tells Docker to run the image was built in the previous step
)

# if you are curious you can paste this string into a terminal window after the command 'docker':
docker_cmd
```

```
## run --detach  --name sql-pet --publish 5432:5432 --mount type=bind,source="/Users/jds/Documents/Library/
```

```
system2("docker", docker_cmd, stdout = TRUE, stderr = TRUE)
```

```
## [1] "3fea949dfb0958c1497ae8a18c9f21d6cf5867b8d6cc285cf153026aa707b335"
```

6.6 Connect to Postgres with R

Use the DBI package to connect to PostgreSQL.

```
con <- sp_get_postgres_connection(user = Sys.getenv("DEFAULT_POSTGRES_USER_NAME"),
                          password = Sys.getenv("DEFAULT_POSTGRES_PASSWORD"),
                          dbname = "dvdrental",
                          seconds_to_test = 10)
```

List the tables in the database and the fields in one of those tables. Then disconnect from the database.

```
dbListTables(con)
```

```
##  [1] "actor_info"                 "customer_list"
##  [3] "film_list"                  "nicer_but_slower_film_list"
##  [5] "sales_by_film_category"     "staff"
##  [7] "sales_by_store"             "staff_list"
##  [9] "category"                   "film_category"
## [11] "country"                    "actor"
## [13] "language"                   "inventory"
## [15] "payment"                    "rental"
## [17] "city"                       "store"
## [19] "film"                       "address"
## [21] "film_actor"                 "customer"
```

```
dbListFields(con, "rental")
```

```
## [1] "rental_id"    "rental_date"  "inventory_id" "customer_id"
## [5] "return_date"  "staff_id"     "last_update"
```

```
dbDisconnect(con)
```

6.7 Stop and start to demonstrate persistence

Stop the container

```
sp_docker_stop("sql-pet")
```

```
## [1] "sql-pet"
```

Restart the container and verify that the dvdrental tables are still there

```
sp_docker_start("sql-pet")

con <- sp_get_postgres_connection(user = Sys.getenv("DEFAULT_POSTGRES_USER_NAME"),
                         password = Sys.getenv("DEFAULT_POSTGRES_PASSWORD"),
                         dbname = "dvdrental",
                         seconds_to_test = 10)
```

Check that you can still see the fields in the `rental` table:

```
dbListFields(con, "rental")
```

```
## [1] "rental_id"    "rental_date"  "inventory_id" "customer_id"
## [5] "return_date"  "staff_id"     "last_update"
```

6.8 Cleaning up

Always have R disconnect from the database when you're done.

```
dbDisconnect(con)
```

Stop the container and show that the container is still there, so can be started again.

```
sp_docker_stop("sql-pet")
```

```
## [1] "sql-pet"
```

```
# show that the container still exists even though it's not running
sp_show_all_docker_containers()
```

```
## [1] "CONTAINER ID      IMAGE             COMMAND                CREATED         STATUS                    POR
## [2] "3fea949dfb09      postgres-dvdrental  \"docker-entrypoint.s…\"  7 seconds ago     Exited (0) Less t
```

Next time, you can just use this command to start the container:

```
sp_docker_start("sql-pet")
```

And once stopped, the container can be removed with:

```
sp_check_that_docker_is_up("sql-pet)
```

6.9 Using the `sql-pet` container in the rest of the book

After this point in the book, we assume that Docker is up and that we can always start up our *sql-pet database* with:

```
sp_docker_stop("sql-pet")
```

Chapter 7

Mapping your local environment (10)

7.1 Basics

- Keeping passwords secure.
- Coverage in this book. There are many SQL tutorials that are available. For example, we are drawing some materials from a tutorial we recommend. In particular, we will not replicate the lessons there, which you might want to complete. Instead, we are showing strategies that are recommended for R users. That will include some translations of queries that are discussed there.

7.2 Ask yourself, what are you aiming for?

- Differences between production and data warehouse environments.
- Learning to keep your DBAs happy:
  - You are your own DBA in this simulation, so you can wreak havoc and learn from it, but you can learn to be DBA-friendly here.
  - In the end it's the subject-matter experts that understand your data, but you have to work with your DBAs first.

7.3 Get some basic information about your database

Assume that the Docker container with PostgreSQL and the dvdrental database are ready to go. Start up the `docker-pet` container

```
sp_docker_start("sql-pet")
```

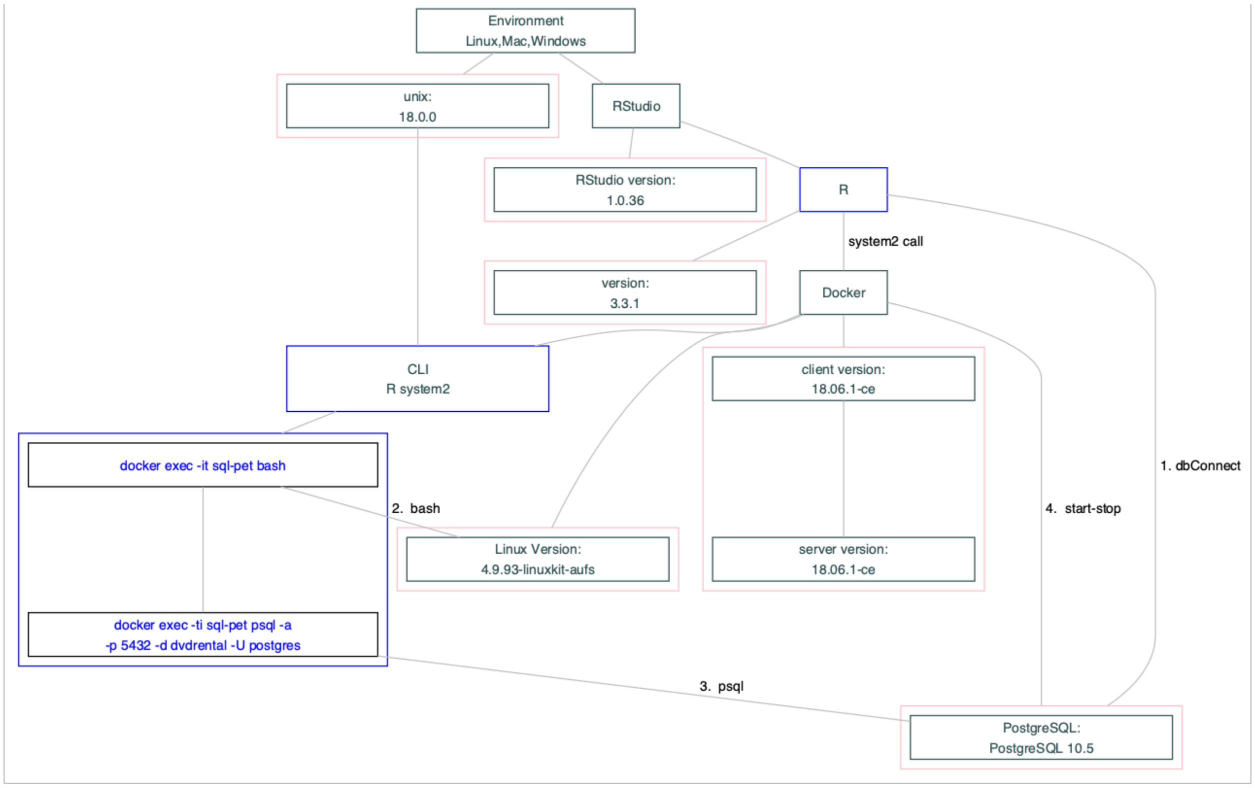
Now connect to the `dvdrental` database with R.
The following code block confirms that one can connect to the Postgres database. The connection is needed for some of the examples/exercises used in this section. If the connection is successful, the output is `<PostgreSQLConnection>`.

```
con <- sp_get_postgres_connection(
  user = Sys.getenv("DEFAULT_POSTGRES_USER_NAME"),
  password = Sys.getenv("DEFAULT_POSTGRES_PASSWORD"),
  dbname = "dvdrental",
  seconds_to_test = 10
)
con
```

```
## <PqConnection> dvdrental@localhost:5432
```

7.4 Tutorial Environment

Below is a high level diagram of our tutorial environment. The single black or blue boxed items are the apps running on your PC, (Linux, Mac, Windows), RStudio, R, Docker, and CLI, a command line interface. The red boxed items are the versions of the applications shown. The labels are to the right of the line.



7.5 Communicating with Docker Applications

One assumption we made is that most users use `RStudio` to interface with `R`. The four take aways from the diagram above are labeled:

7.5.1 dbConnect

R-SQL processing, the purpose of this tutorial, is performed via a database connection. This should be a simple task, but often turns out to take a lot of time to actually get it to work. We assume that your final write ups are done in some flavor of an Rmd document and others will have access to the database to confirm or further your analysis.

One focus of this tutorial is SQL processing through a dbConnection and we will come back to this in a future section. The remainder of this section focuses on some specific Docker commands.

7.5.2 bash

The Docker container runs on top of a small Linux kernel foot print. Since Mac and Linux users run a version of Linux already, they may want to poke around the Docker environment. Below is the CLI command to start up a bash session, execute a version of hello world, and exit the `bash` session.

(In this and subsequent example, an initial `$` represents your system prompt, which varies according to operating system and local environment.)

In your computer's command prompt:

```
$ docker exec -ti sql-pet bash
```

Inside the `bash` (UNIX command) environment:

```
$ echo "'hello world'" talking to you live from a bash shell session within Docker!

'hello world' talking to you live from a bash shell session within Docker!
$ exit
```

Now back at your computer command prompt with:

```
$ exit
```

Note that the user in the example is root. Root has all priviledges and can destroy the Docker environment.

7.5.3 psql

For users comfortable executing SQL from a command line directly against the database, one can run the `psql` application directly. Below is the CLI command to start up `psql` session, execute a version of hello world, and quitting the `psql` version.

In your computer's command prompt:

```
$ docker exec -ti sql-pet psql -a -p 5432 -d dvdrental -U postgres
```

That executes a postreSQL program in docker called `psql`, which is a command line interface to postgreSQL. `psql` responds with:

```
psql (10.5 (Debian 10.5-1.pgdg90+1))
Type "help" for help.
```

You enter:

```
`select '"hello world" talking to you live from postgres inside Docker!' hello;`
```

All SQL commands need to end with a semi-colon. `psql` responds with:

```
                                hello
-------------------------------------------------------------------------
 "hello world" talking to you live from postgres inside Docker!
(1 row)
```

To exit `psql`, enter:

```
    \q
```

The docker bash and psql command options are optional for this tutorial, but open up a gateway to some very powerful programming techniques for future exploration.

7.5.4 start-stop

Docker has about 44 commands. We are interested in only those related to Postgres status, started, stopped, and available. In this tutorial, complete docker commands are printed out before being executed via a `system2` call. In the event that a code block fails, one can copy and paste the docker command into your local CLI and see if Docker is returning additional information.

7.6 Exercises

Docker containers have a small foot print. In our container, we are running a limited Linux kernel and a Postgres database. To show how tiny the docker environment is, we will look at all the processes running inside Docker and the top level file structure.

7.6.1 Docker Help

Typing `docker` at the command line will print up a summary of all available `docker` commands. Below are the docker commands used in the exercises.

```
Commands:
  ps          List containers
  start       Start one or more stopped containers
  stop        Stop one or more running containers
```

The general format for a Docker command is

```
docker [OPTIONS] COMMAND ARGUMENTS
```

Below is the output for the Docker exec help command which was used in the `bash` and `psql` command examples above and for an exercise below.

```
$ docker help exec

Usage:  docker exec [OPTIONS] CONTAINER COMMAND [ARG...]

Run a command in a running container

Options:
  -d, --detach               Detached mode: run command in the background
      --detach-keys string   Override the key sequence for detaching a
                             container
  -e, --env list             Set environment variables
  -i, --interactive          Keep STDIN open even if not attached
      --privileged           Give extended privileges to the command
  -t, --tty                  Allocate a pseudo-TTY
  -u, --user string          Username or UID (format:
                             <name|uid>[:<group|gid>])
  -w, --workdir string       Working directory inside the container
```

In the following exercies, use the `-i` option and the CONTAINER = `sql-pet`.

Start up R/RStudio and convert the CLI command to an R/RStudio command

#	Question	Docker CLI Command	R RStudio command	Local Command LINE
1	How many processes are running inside the Docker container?	docker exec -i sql-pet ps -eF		
1a	How many process are running on your local machine?			widows: tasklist Mac/Linux: ps -ef
2	What is the total number of files and directories in Docker?	docker exec -i sql-pet ls -al		
2a	What is the total number of files and directories on your local machine?			
3	Is Docker Running?	docker version		
3a	What are your Client and Server Versions?			
4	Does Postgres exist in the container?	docker ps -a		
4a	What is the status of Postgres?	docker ps -a		
4b	What is the size of Postgres?	docker images		
4c	What is the size of your laptop OS			https://www.quora.com/What-is-the-actual-size-of-Windows
5	If sql-pet status is Up, How do I stop it?	docker stop sql-pet		
5a	If sql-pet status is Exited, How do I start it?	docker start sql-pet		

In	Dplyr Function	description	SQL Clause	Notes	Category
Y	arrange()	Arrange rows by variables	ORDER BY		Basic single-table verbs
Y?	distinct()	Return rows with matching conditions	SELECT distinct *		Basic single-table verbs
Y	select() rename()	Select/rename variables by name	SELECT column_name alias_name		Basic single-table verbs

In	Dplyr Function	description	SQL Clause	Notes	Category
N	pull()	Pull out a single variable	SELECT column_name;		Basic single-table verbs
Y	mutate() transmute()	Add new variables	SELECT computed_value computed_name		Basic single-table verbs
Y	summarise() summarize()	Reduces multiple values down to a single value	SELECT aggregate_functions GROUP BY		Basic single-table verbs
N	group_by() ungroup()	Objects exported from other packages	GROUP BY no ungroup		Basic single-table verbs
N	distinct()	Select distinct/unique rows	SELECT distinct {colname1,...colnamen}		Basic single-table verbs
N	do()	Do anything	NA		Basic single-table verbs
N	sample_n() sample_frac()	Sample n rows from a table	ORDER BY RANDOM() LIMIT 10		Basic single-table verbs
N	slice()	Select rows by position	SELECT row_number() over (partition by expression(s) order_by exp)		Basic single-table verbs
Y	tally() count() add_tally() add_count()	Count/tally observations by group	GROUP BY		Single-table helpers
Y	top_n()	Select top (or bottom) n rows (by value)	ORDER BY VALUE {DESC} LIMIT 10		Single-table helpers
N	arrange_all() arrange_at() arrange_if()	Arrange rows by a selection of variables	ORDER BY		scoped-Operate on a selection of variables
N	filter_all() filter_if() filter_at()	Filter within a selection of variables			scoped-Operate on a selection of variables

In	Dplyr Function	description	SQL Clause	Notes	Category
N	group_by_all() group_by_at() group_by_if()	Group by a selection of variables			scoped-Operate on a selection of variables
N	select_all() rename_all() select_if() rename_if() select_at() rename_at()	Select and rename a selection of variables			scoped-Operate on a selection of variables
N	summarise_all() summarise_if() summarise_at() summarize_all() summarize_if() summarize_at() mutate_all() mutate_if() mutate_at() transmute_all() transmute_if() transmute_at()	Summarise and mutate multiple columns.			scoped-Operate on a selection of variables
N	all_vars() any_vars()	Apply predicate to all variables			scoped-Operate on a selection of variables
N	vars()	Select variables			scoped-Operate on a selection of variables
N	funs()	Create a list of functions calls.			scoped-Operate on a selection of variables
N	all_equal() all.equal()	Flexible equality comparison for data frames			Two-table verbs
N	bind_rows() bind_cols() combine()	Efficiently bind multiple data frames by row and column			Two-table verbs
N	intersect() union() union_all() setdiff() setequal()	Set operations			Two-table verbs

In	Dplyr Function	description	SQL Clause	Notes	Category
N	inner_join() left_join() right_join() full_join() semi_join() anti_join()	Join two tbls together			Two-table verbs
N	inner_join() left_join() right_join() full_join() semi_join() anti_join()	Join data frame tbls			Two-table verbs
N	auto_copy()	Copy tables to same source, if necessary			Remote tables
N	compute() collect() collapse()	Force computation of a database query			Remote tables
N	copy_to()	Copy a local data frame to a remote src			Remote tables
N	ident()	Flag a character vector as SQL identifiers			Remote tables
N	explain() show_query()	Explain details of a tbl			Remote tables
N	tbl() is.tbl() as.tbl()	Create a table from a data source			Remote tables
N	src_mysql() src_postgres() src_sqlite()	Source for database backends			Remote tables
N	sql()	SQL escaping.			Remote tables
N	groups() group_vars()	Return grouping variables			Metadata
N	between()	Do values in a numeric vector fall in specified range?			Vector functions
N	case_when()	A general vectorised if			Vector functions
N	coalesce()	Find first non-missing element			Vector functions
N	cumall() cumany() cummean()	Cumulativate versions of any, all, and mean			Vector functions
N	desc()	Descending order			Vector functions
N	if_else()	Vectorised if			Vector functions
N	lead() lag()	Lead and lag.			Vector functions
N	order_by()	A helper function for ordering window function output			Vector functions
N	n()	The number of observations in the current group.			Vector functions

In	Dplyr Function	description	SQL Clause	Notes	Category
N	n_distinct()	Efficiently count the number of unique values in a set of vector			Vector functions
N	na_if()	Convert values to NA			Vector functions
N	near()	Compare two numeric vectors			Vector functions
N	nth() first() last()	Extract the first, last or nth value from a vector			Vector functions
N	row_number() ntile() min_rank() dense_rank() percent_rank() cume_dist()	Windowed rank functions.			Vector functions
N	recode() recode_factor()	Recode values			Vector functions
N	band_members band_instruments band_instruments2	Band membership			Data
N	nasa	NASA spatio-temporal data			Data
N	starwars	Starwars characters			Data
N	storms	Storm tracks data			Data
N	tbl_cube()	A data cube tbl			Other backends
N	as.table() as.data.frame() as_data_frame()	Coerce a tbl_cube to other data structures			Other backends
N	as.tbl_cube()	Coerce an existing data structure into a tbl_cube			Other backends
N	rowwise()	Group input by rows			Other backends

Chapter 8

Introduction to DBMS queries (11)

The following packages are used in this chapter:

```
library(tidyverse)
library(DBI)
library(RPostgres)
library(dbplyr)
require(knitr)
library(bookdown)
library(sqlpetr)
```

Assume that the Docker container with PostgreSQL and the dvdrental database are ready to go.

```
sp_docker_start("sql-pet")
```

Connect to the database:

```
con <- sp_get_postgres_connection(
  user = Sys.getenv("DEFAULT_POSTGRES_USER_NAME"),
  password = Sys.getenv("DEFAULT_POSTGRES_PASSWORD"),
  dbname = "dvdrental",
  seconds_to_test = 10
)
```

8.1 Getting data from the database

As we show later on, the database serves as a store of data and as an engine for sub-setting, joining, and computation on the data. We begin with getting data from the dbms, or "downloading" data.

8.1.1 Finding out what's there

We've already seen the simplest way of getting a list of tables in a database with `DBI` functions that list tables and fields. Generate a vector listing the (public) tables in the database:

```
tables <- DBI::dbListTables(con)
tables
```

```
## [1] "actor_info"                "customer_list"
## [3] "film_list"                 "nicer_but_slower_film_list"
## [5] "sales_by_film_category"    "staff"
```

```
##  [7] "sales_by_store"             "staff_list"
##  [9] "category"                   "film_category"
## [11] "country"                    "actor"
## [13] "language"                   "inventory"
## [15] "payment"                    "rental"
## [17] "city"                       "store"
## [19] "film"                       "address"
## [21] "film_actor"                 "customer"
```

Print a vector with all the fields (or columns or variables) in one specific table:

```
DBI::dbListFields(con, "rental")
```

```
## [1] "rental_id"    "rental_date"  "inventory_id" "customer_id"
## [5] "return_date"  "staff_id"     "last_update"
```

8.1.2 Listing all the fields for all the tables

The first example, `DBI::dbListTables(con)` returned 22 tables and the second example, `DBI::dbListFields(con, "rental")` returns 7 fields. Here we combine the two calls to return a list of tables which has a list of all the fields in the table. The code block just shows the first two tables.

Use the

```
table_columns <- lapply(tables, dbListFields, conn = con)

# rename each list [[1]] ... [[22]] to meaningful table name
names(table_columns) <- tables

head(table_columns)
```

```
## $actor_info
## [1] "actor_id"   "first_name" "last_name"  "film_info"
##
## $customer_list
## [1] "id"       "name"     "address"  "zip code" "phone"    "city"
## [7] "country"  "notes"    "sid"
##
## $film_list
## [1] "fid"         "title"       "description" "category"    "price"
## [6] "length"      "rating"      "actors"
##
## $nicer_but_slower_film_list
## [1] "fid"         "title"       "description" "category"    "price"
## [6] "length"      "rating"      "actors"
##
## $sales_by_film_category
## [1] "category"    "total_sales"
##
## $staff
##  [1] "staff_id"    "first_name"  "last_name"   "address_id"  "email"
##  [6] "store_id"    "active"      "username"    "password"    "last_update"
## [11] "picture"
```

Later on we'll discuss how to get more extensive data about each table and column from the database's own store of metadata using a similar technique. As we go further the issue of scale will come up again and again:

you need to be careful about how much data a call to the dbms will return, whether it's a list of tables or a table that could have millions of rows.

8.1.3 Connect with people who own, generate, or are the subjects of the data

A good chat with people who own the data, generate it, or are the subjects can generate insights and set the context for your investigation of the database. The purpose for collecting the data or circumsances where it was collected may be burried far afield in an organization, but *usually someone knows*. The metadata discussed in a later chapter is essential but will only take you so far.

There are different ways of just **looking at the data**, which we explore below.

8.1.4 Downloading an entire table

There are many different methods of getting data from a DBMS, and we'll explore the different ways of controlling each one of them.

`DBI::dbReadTable` will download an entire table into an R tibble.

```
rental_tibble <- DBI::dbReadTable(con, "rental")
str(rental_tibble)
```

```
## 'data.frame':    16044 obs. of  7 variables:
##  $ rental_id   : int  2 3 4 5 6 7 8 9 10 11 ...
##  $ rental_date : POSIXct, format: "2005-05-24 22:54:33" "2005-05-24 23:03:39" ...
##  $ inventory_id: int  1525 1711 2452 2079 2792 3995 2346 2580 1824 4443 ...
##  $ customer_id : int  459 408 333 222 549 269 239 126 399 142 ...
##  $ return_date : POSIXct, format: "2005-05-28 19:40:33" "2005-06-01 22:12:39" ...
##  $ staff_id    : int  1 1 2 1 1 2 2 1 2 2 ...
##  $ last_update : POSIXct, format: "2006-02-16 02:30:53" "2006-02-16 02:30:53" ...
```

That's very simple, but if the table is large it may not be a good idea, since R is designed to keep the entire table in memory. Note that the first line of the str() output reports the total number of observations.

8.1.5 A table object that can be reused

The `dplyr::tbl` function gives us more control over access to a table by enabling control over which columns and rows to download. It creates an object that might **look** like a data frame, but it's actually a list object that `dplyr` uses for constructing queries and retrieving data from the DBMS.

```
rental_table <- dplyr::tbl(con, "rental")
```

Consider the structure of the connection object:

```
str(rental_table)
```

```
## List of 2
##  $ src:List of 2
##   ..$ con  :Formal class 'PqConnection' [package "RPostgres"] with 3 slots
##   .. .. ..@ ptr     :<externalptr>
##   .. .. ..@ bigint  : chr "integer64"
##   .. .. ..@ typnames:'data.frame':   437 obs. of  2 variables:
##   .. .. .. ..$ oid    : int [1:437] 16 17 18 19 20 21 22 23 24 25 ...
##   .. .. .. ..$ typname: chr [1:437] "bool" "bytea" "char" "name" ...
##   ..$ disco: NULL
##   ..- attr(*, "class")= chr [1:3] "src_dbi" "src_sql" "src"
```

```
##  $ ops:List of 2
##   ..$ x   : 'ident' chr "rental"
##   ..$ vars: chr [1:7] "rental_id" "rental_date" "inventory_id" "customer_id" ...
##   ..- attr(*, "class")= chr [1:3] "op_base_remote" "op_base" "op"
##  - attr(*, "class")= chr [1:4] "tbl_dbi" "tbl_sql" "tbl_lazy" "tbl"
```

Notice that the first list contains the source connection information. Among other things it contains a list of variables/columns in the table:

```
rental_table$ops$vars
```

```
## [1] "rental_id"    "rental_date"  "inventory_id" "customer_id"
## [5] "return_date"  "staff_id"     "last_update"
```

8.1.6 Paradigm Shift: Lazy Execution

R and `dplyr` is designed to be both lazy and smart. Lazy execution affects when a donwload happens and when processing occurs on the dbms server side. R retrieves the full data set when explicityly told to do so via the `collect` verb, otherwise it returns only 10 rows. And `dplyr` tries to get as much work done on the server side as possible before downloading anything. All of this is a key paradigm shift for those new to working with databases using R and `dplyr`, especially if they have been working in a straight SQL environment.

explain why this matters here

In the code blocks below, we demonstrate three ways to check if `dplyr` has performed lazy/delayed execution.

1. Display the object.
2. nrow(object)
3. Check the pipe.

```
rental_table <- dplyr::tbl(con, "rental")
rental_table
```

```
## # Source:   table<rental> [?? x 7]
## # Database: postgres [postgres@localhost:5432/dvdrental]
##    rental_id rental_date         inventory_id customer_id
##        <int> <dttm>                     <int>       <int>
##  1         2 2005-05-24 22:54:33         1525         459
##  2         3 2005-05-24 23:03:39         1711         408
##  3         4 2005-05-24 23:04:41         2452         333
##  4         5 2005-05-24 23:05:21         2079         222
##  5         6 2005-05-24 23:08:07         2792         549
##  6         7 2005-05-24 23:11:53         3995         269
##  7         8 2005-05-24 23:31:46         2346         239
##  8         9 2005-05-25 00:00:40         2580         126
##  9        10 2005-05-25 00:02:21         1824         399
## 10        11 2005-05-25 00:09:02         4443         142
## # ... with more rows, and 3 more variables: return_date <dttm>,
## #   staff_id <int>, last_update <dttm>
```

```
head(rental_table, n = 25)
```

```
## # Source:   lazy query [?? x 7]
## # Database: postgres [postgres@localhost:5432/dvdrental]
##    rental_id rental_date         inventory_id customer_id
##        <int> <dttm>                     <int>       <int>
##  1         2 2005-05-24 22:54:33         1525         459
```

```
## 2         3 2005-05-24 23:03:39         1711         408
## 3         4 2005-05-24 23:04:41         2452         333
## 4         5 2005-05-24 23:05:21         2079         222
## 5         6 2005-05-24 23:08:07         2792         549
## 6         7 2005-05-24 23:11:53         3995         269
## 7         8 2005-05-24 23:31:46         2346         239
## 8         9 2005-05-25 00:00:40         2580         126
## 9        10 2005-05-25 00:02:21         1824         399
## 10       11 2005-05-25 00:09:02         4443         142
## # ... with more rows, and 3 more variables: return_date <dttm>,
## #   staff_id <int>, last_update <dttm>
```

At the top of the output look for the dimensions, [?? x columns] or at the bottom for '… with more rows'

Notice that **head** should return 25 rows, but only shows the 10 rows it has can retrieve.

```
nrow(rental_table)
```

```
## [1] NA
```

The the `rental_table` is smart enough to returns `NA` when passed to `nrow` so no execution is performed.

```
rental_table %>% dplyr::summarise(n = n())
```

```
## # Source:   lazy query [?? x 1]
## # Database: postgres [postgres@localhost:5432/dvdrental]
##   n
##   <S3: integer64>
## 1 16044
```

```
rental_table %>% dplyr::summarise(n = n()) %>% show_query()
```

```
## <SQL>
## SELECT COUNT(*) AS "n"
## FROM "rental"
```

The `dplyr::summarise` verb does not force R to download the whole table. It **processes** the whole table by counting all the rows on the dbms side and then downloads one number.

Next we give an example where R gets busy and returns the full data set.

```
rental_table <- dplyr::tbl(con, "rental") # Lazy

collect_rental_table <- rental_table %>% collect() # Busy
collect_rental_table
```

```
## # A tibble: 16,044 x 7
##    rental_id rental_date         inventory_id customer_id
##        <int> <dttm>                     <int>       <int>
## 1          2 2005-05-24 22:54:33         1525         459
## 2          3 2005-05-24 23:03:39         1711         408
## 3          4 2005-05-24 23:04:41         2452         333
## 4          5 2005-05-24 23:05:21         2079         222
## 5          6 2005-05-24 23:08:07         2792         549
## 6          7 2005-05-24 23:11:53         3995         269
## 7          8 2005-05-24 23:31:46         2346         239
## 8          9 2005-05-25 00:00:40         2580         126
## 9         10 2005-05-25 00:02:21         1824         399
## 10        11 2005-05-25 00:09:02         4443         142
## # ... with 16,034 more rows, and 3 more variables: return_date <dttm>,
```

```
## #   staff_id <int>, last_update <dttm>
```

At the top of the output, `# A tibble: 16,044 x 7` and at the bottom of the output, `# ... with 16,034 more rows` we see that `dplyr::tbl` returned all the rows associated with `collect_rental_table`. See [Controlling number of rows returned] for additional R examples showing R getting to work, and return some or all the rows.

See more example of lazy execution can be found Here.

8.1.7 Controlling the number of rows returned

The `collect` function triggers the creation of a tibble and controls the number of rows that the DBMS sends to R. Note that in the following examples, the object dimensions are known.

```
rental_table %>% collect(n = 3) %>% head()
```

```
## # A tibble: 3 x 7
##   rental_id rental_date         inventory_id customer_id
##       <int> <dttm>                     <int>       <int>
## 1         2 2005-05-24 22:54:33         1525         459
## 2         3 2005-05-24 23:03:39         1711         408
## 3         4 2005-05-24 23:04:41         2452         333
## # ... with 3 more variables: return_date <dttm>, staff_id <int>,
## #   last_update <dttm>
```

In this case the `collect` function triggers the execution of a query that counts the number of records in the table by `staff_id`:

```
rental_table %>%
  count(staff_id) %>%
  collect()
```

```
## # A tibble: 2 x 2
##   staff_id n
##      <int> <S3: integer64>
## 1        2 8004
## 2        1 8040
```

The `collect` function affects how much is downloaded, not how many rows the DBMS needs to process the query. This query processes all of the rows in the table but only displays one row of output.

```
rental_table %>%
  count(staff_id) %>%
  collect(n = 1)
```

```
## # A tibble: 1 x 2
##   staff_id n
##      <int> <S3: integer64>
## 1        2 8004
```

8.1.8 Random rows from the dbms

When the dbms contains many rows, a sample of the data may be plenty for your purposes. Although `dplyr` has nice functions to sample a data frame that's already in R (e.g., the `sample_n` and `sample_frac` functions), to get a sample from the dbms we have to use `dbGetQuery` to send native SQL to the database. To peak ahead, here is one example of a query that retrieves 20 rows from a 1% sample:

```
one_percent_sample <- DBI::dbGetQuery(
  con,
  "SELECT rental_id, rental_date, inventory_id, customer_id FROM rental TABLESAMPLE SYSTEM(1) LIMIT 20;
  "
)

one_percent_sample
```

```
##    rental_id         rental_date inventory_id customer_id
## 1      10599 2005-08-01 14:23:58         2422         271
## 2      10600 2005-08-01 14:25:21         3900         294
## 3      10601 2005-08-01 14:25:40         2843         420
## 4      10602 2005-08-01 14:30:23         1506         111
## 5      10603 2005-08-01 14:30:35         4024         394
## 6      10604 2005-08-01 14:35:08         2833         250
## 7      10605 2005-08-01 14:36:26          680         341
## 8      10606 2005-08-01 14:39:15           81         335
## 9      10607 2005-08-01 14:44:43         3999         438
## 10     10608 2005-08-01 14:48:41         3835         381
## 11     10609 2005-08-01 14:48:45         2587           5
## 12     10610 2005-08-01 14:49:41         1865         396
## 13     10611 2005-08-01 14:53:52          957         135
## 14     10612 2005-08-01 14:55:31          287         554
## 15     10613 2005-08-01 14:56:14         4357         527
## 16     10614 2005-08-01 14:57:00          232         533
## 17     10615 2005-08-01 14:58:14         2639          34
## 18     10616 2005-08-01 14:59:50         1094          20
## 19     10617 2005-08-01 15:05:52         4344         476
## 20     10618 2005-08-01 15:06:38         3729         386
```

8.1.9 Sub-setting variables

A table in the dbms may not only have many more rows than you want and also many more columns. The `select` command controls which columns are retrieved.

```
rental_table %>% select(rental_date, return_date) %>% head()
```

```
## # Source:   lazy query [?? x 2]
## # Database: postgres [postgres@localhost:5432/dvdrental]
##   rental_date         return_date
##   <dttm>              <dttm>
## 1 2005-05-24 22:54:33 2005-05-28 19:40:33
## 2 2005-05-24 23:03:39 2005-06-01 22:12:39
## 3 2005-05-24 23:04:41 2005-06-03 01:43:41
## 4 2005-05-24 23:05:21 2005-06-02 04:33:21
## 5 2005-05-24 23:08:07 2005-05-27 01:32:07
## 6 2005-05-24 23:11:53 2005-05-29 20:34:53
```

We won't discuss `dplyr` methods for sub-setting variables, deriving new ones, or sub-setting rows based on the values found in the table because they are covered well in other places, including:

- Comprehensive reference: https://dplyr.tidyverse.org/
- Good tutorial: https://suzan.rbind.io/tags/dplyr/

In practice we find that, **renaming variables** is often quite important because the names in an SQL database might not meet your needs as an analyst. In "the wild" you will find names that are ambiguous or overly specified, with spaces in them, and other problems that will make them difficult to use in R. It is good practice to do whatever renaming you are going to do in a predictable place like at the top of your code. The names in the `dvdrental` database are simple and clear, but if they were not, you might rename them for subsequent use in this way:

```
renamed_rental_table <- dplyr::tbl(con, "rental") %>%
  rename(rental_id_number = rental_id, inventory_id_number = inventory_id)

renamed_rental_table %>%
  select(rental_id_number, rental_date, inventory_id_number) %>%
  head()
```

```
## # Source:   lazy query [?? x 3]
## # Database: postgres [postgres@localhost:5432/dvdrental]
##   rental_id_number rental_date         inventory_id_number
##              <int> <dttm>                            <int>
## 1                2 2005-05-24 22:54:33                1525
## 2                3 2005-05-24 23:03:39                1711
## 3                4 2005-05-24 23:04:41                2452
## 4                5 2005-05-24 23:05:21                2079
## 5                6 2005-05-24 23:08:07                2792
## 6                7 2005-05-24 23:11:53                3995
```

8.1.10 Examining `dplyr`'s SQL query and re-using SQL code

The `show_query` function shows how `dplyr` is translating your query to the dialect of the target dbms:

```
rental_table %>%
  count(staff_id) %>%
  show_query()
```

```
## <SQL>
## SELECT "staff_id", COUNT(*) AS "n"
## FROM "rental"
## GROUP BY "staff_id"
```

Here is an extensive discussion of how `dplyr` code is translated into SQL:

- https://dbplyr.tidyverse.org/articles/sql-translation.html

The SQL code can submit the same query directly to the DBMS with the `DBI::dbGetQuery` function:

```
DBI::dbGetQuery(
  con,
  'SELECT "staff_id", COUNT(*) AS "n"
   FROM "rental"
   GROUP BY "staff_id";
  '
)
```

```
##   staff_id    n
## 1        2 8004
## 2        1 8040
```

<<smy We haven't investigated this, but it looks like `dplyr` collect() function triggers a call simmilar to the dbGetQuery call above. The default `dplyr` behavior looks like dbSendQuery() and dbFetch() model is used.>>

When you create a report to run repeatedly, you might want to put that query into R markdown. That way you can also execute that SQL code in a chunk with the following header:

{sql, connection=con, output.var = "query_results"}

```
SELECT "staff_id", COUNT(*) AS "n"
FROM "rental"
GROUP BY "staff_id";
```

Rmarkdown stored that query result in a tibble:

```
query_results
```

```
##   staff_id    n
## 1        2 8004
## 2        1 8040
```

8.2 Examining a single table with R

Dealing with a large, complex database highlights the utility of specific tools in R. We include brief examples that we find to be handy:

- Base R structure: `str`
- printing out some of the data: `datatable`, `kable`, and `View`
- summary statistics: `summary`
- `glimpse` oin the `tibble` package, which is included in the `tidyverse`
- `skim` in the `skimr` package

8.2.1 `str` - a base package workhorse

`str` is a workhorse function that lists variables, their type and a sample of the first few variable values.

```
str(rental_tibble)
```

```
## 'data.frame':    16044 obs. of  7 variables:
##  $ rental_id   : int  2 3 4 5 6 7 8 9 10 11 ...
##  $ rental_date : POSIXct, format: "2005-05-24 22:54:33" "2005-05-24 23:03:39" ...
##  $ inventory_id: int  1525 1711 2452 2079 2792 3995 2346 2580 1824 4443 ...
##  $ customer_id : int  459 408 333 222 549 269 239 126 399 142 ...
##  $ return_date : POSIXct, format: "2005-05-28 19:40:33" "2005-06-01 22:12:39" ...
##  $ staff_id    : int  1 1 2 1 1 2 2 1 2 2 ...
##  $ last_update : POSIXct, format: "2006-02-16 02:30:53" "2006-02-16 02:30:53" ...
```

8.2.2 Always just look at your data with `head`, `View`, or `kable`

There is no substitute for looking at your data and R provides several ways to just browse it. The `head` function controls the number of rows that are displayed. Note that tail does not work against a database object. In every-day practice you would look at more than the default 6 rows, but here we wrap `head` around the data frame:

```
sp_print_df(head(rental_tibble))
```

rental_id	rental_date	inventory_id	customer_id	return_date	staff_id	last_update
2	2005-05-24 22:54:33	1525	459	2005-05-28 19:40:33	1	2006-02-16 02:30:53
3	2005-05-24 23:03:39	1711	408	2005-06-01 22:12:39	1	2006-02-16 02:30:53
4	2005-05-24 23:04:41	2452	333	2005-06-03 01:43:41	2	2006-02-16 02:30:53
5	2005-05-24 23:05:21	2079	222	2005-06-02 04:33:21	1	2006-02-16 02:30:53
6	2005-05-24 23:08:07	2792	549	2005-05-27 01:32:07	1	2006-02-16 02:30:53
7	2005-05-24 23:11:53	3995	269	2005-05-29 20:34:53	2	2006-02-16 02:30:53

8.2.3 The `summary` function in `base`

The basic statistics that the base package `summary` provides can serve a unique diagnostic purpose in this context. For example, the following output shows that `rental_id` is a sequential number from 1 to 16,049 with no gaps. The same is true of `inventory_id`. The number of NA's is a good first guess as to the number of dvd's rented out or lost on 2005-09-02 02:35:22.

```
summary(rental_tibble)
```

```
##    rental_id      rental_date                    inventory_id 
##  Min.   :    1   Min.   :2005-05-24 22:53:30   Min.   :   1  
##  1st Qu.: 4014   1st Qu.:2005-07-07 00:58:40   1st Qu.:1154  
##  Median : 8026   Median :2005-07-28 16:04:32   Median :2291  
##  Mean   : 8025   Mean   :2005-07-23 08:13:34   Mean   :2292  
##  3rd Qu.:12037   3rd Qu.:2005-08-17 21:16:23   3rd Qu.:3433  
##  Max.   :16049   Max.   :2006-02-14 15:16:03   Max.   :4581  
##                                                               
##   customer_id     return_date                      staff_id    
##  Min.   :  1.0   Min.   :2005-05-25 23:55:21   Min.   :1.000  
##  1st Qu.:148.0   1st Qu.:2005-07-10 15:49:36   1st Qu.:1.000  
##  Median :296.0   Median :2005-08-01 19:45:29   Median :1.000  
##  Mean   :297.1   Mean   :2005-07-25 23:58:03   Mean   :1.499  
##  3rd Qu.:446.0   3rd Qu.:2005-08-20 23:35:55   3rd Qu.:2.000  
##  Max.   :599.0   Max.   :2005-09-02 02:35:22   Max.   :2.000  
##                  NA's   :183                                  
##   last_update                 
##  Min.   :2006-02-15 21:30:53  
##  1st Qu.:2006-02-16 02:30:53  
##  Median :2006-02-16 02:30:53  
##  Mean   :2006-02-16 02:31:31  
##  3rd Qu.:2006-02-16 02:30:53  
##  Max.   :2006-02-23 09:12:08  
## 
```

8.2.4 The `glimpse` function in the `tibble` package

The `tibble` package's `glimpse` function is a more compact version of `str`:

```
tibble::glimpse(rental_tibble)
```

```
## Observations: 16,044
## Variables: 7
## $ rental_id    <int> 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 1...
## $ rental_date  <dttm> 2005-05-24 22:54:33, 2005-05-24 23:03:39, 2005-0...
## $ inventory_id <int> 1525, 1711, 2452, 2079, 2792, 3995, 2346, 2580, 1...
## $ customer_id  <int> 459, 408, 333, 222, 549, 269, 239, 126, 399, 142,...
```

```
## $ return_date  <dttm> 2005-05-28 19:40:33, 2005-06-01 22:12:39, 2005-0...
## $ staff_id     <int> 1, 1, 2, 1, 1, 2, 2, 1, 2, 2, 2, 1, 1, 1, 2, 1, 2...
## $ last_update  <dttm> 2006-02-16 02:30:53, 2006-02-16 02:30:53, 2006-0...
```

8.2.5 The skim function in the skimr package

The `skimr` package has several functions that make it easy to examine an unknown data frame and assess what it contains. It is also extensible.

```
library(skimr)
```

```
##
## Attaching package: 'skimr'

## The following object is masked from 'package:knitr':
##
##     kable
```

```
skim(rental_tibble)
```

```
## Skim summary statistics
##  n obs: 16044
##  n variables: 7
##
## -- Variable type:integer ------------------------------------------------------------
##      variable missing complete     n    mean      sd p0     p25    p50
##   customer_id       0    16044 16044  297.14  172.45  1  148     296
##  inventory_id       0    16044 16044 2291.84 1322.21  1 1154    2291
##     rental_id       0    16044 16044 8025.37 4632.78  1 4013.75 8025.5
##      staff_id       0    16044 16044    1.5     0.5   1    1       1
##       p75  p100     hist
##    446      599
##   3433     4581
##  12037.25 16049
##      2        2
##
## -- Variable type:POSIXct ------------------------------------------------------------
##     variable missing complete     n        min        max     median
##  last_update       0    16044 16044 2006-02-15 2006-02-23 2006-02-16
##  rental_date       0    16044 16044 2005-05-24 2006-02-14 2005-07-28
##  return_date     183    15861 16044 2005-05-25 2005-09-02 2005-08-01
##  n_unique
##         3
##     15815
##     15836
```

```
wide_rental_skim <- skim_to_wide(rental_tibble)
```

8.3 Dividing the work between R on your machine and the DBMS

They work together.

8.3.1 Make the server do as much work as you can

- show_query as a first draft of SQL. May or may not use SQL code submitted directly.

8.3.2 Criteria for choosing between `dplyr` and native SQL

This probably belongs later in the book.

- performance considerations: first get the right data, then worry about performance
- Trade offs between leaving the data in PostgreSQL vs what's kept in R:
  - browsing the data
  - larger samples and complete tables
  - using what you know to write efficient queries that do most of the work on the server

8.3.3 `dplyr` tools

Where you place the `collect` function matters.

```
dbDisconnect(con)
sp_docker_stop("sql-pet")
```

```
## [1] "sql-pet"
```

8.4 DBI Package

In this chapter we touched on a number of functions from the DBI Package. The table below shows other functions in the package. The Chapter column references a section in the book if we have used it.

DBI	Chapter	Call Example/Notes
DBIConnection-class		
dbAppendTable		
dbCreateTable		
dbDisconnect	Every Chapter	
dbExecute	10.4.2	Executes a statement and returns the number of rows affected. dbExecute() comes with a default implementation (which should work with most backends) that calls dbSendStatement(), then dbGetRowsAffected(), ensuring that the result is always free-d by dbClearResult().
dbExistsTable		dbExistsTable(con,'actor')
dbFetch	17.1	dbFecth(rs)
dbGetException		
dbGetInfo		dbGetInfo(con)
dbGetQuery	10.4.1	dbGetQuery(con,'select * from store;')
dbIsReadOnly		dbIsReadOnly(con)
dbIsValid		dbIsValid(con)
dbListFields	8.1.1	DBI::dbListFields(con, "rental")
dbListObjects		dbListObjects(con)
dbListResults		deprecated
dbListTables	8.1.1	DBI::dbListTables(con, "rental")
dbReadTable	8.1.2	DBI::dbReadTable(con, "rental")
dbRemoveTable		
dbSendQuery	17.1	rs <- dbSendQuery(con, "SELECT * FROM mtcars WHERE cyl = 4")

DBI	Chapter	Call Example/Notes
dbSendStatement		The dbSendStatement() method only submits and synchronously executes the SQL data manipulation statement (e.g., UPDATE, DELETE, INSERT INTO, DROP TABLE, …) to the database engine.
dbWriteTable	17.1	dbWriteTable(con, “mtcars”, mtcars, overwrite = TRUE)

8.5 Other resources

- Benjamin S. Baumer, A Grammar for Reproducible and Painless Extract-Transform-Load Operations on Medium Data: https://arxiv.org/pdf/1708.07073

Chapter 9

Explain queries (11a)

This is file `11_dplyr_sql_summary.Rmd`

```
# library(knitr)
dplyr_summary_df <-
    read.delim(here(
    "11_dplyr_sql_summary_table.rmd"),
    header = TRUE,
    sep = '|',
    as.is = TRUE
    )

if (MODE == 'DEMO') {
    View(dplyr_summary_df)
} else {
    kable(dplyr_summary_df)
}
```

In	Dplyr.Function
–	————————————————
Y	arrange()
Y?	distinct()
Y	select() rename()
N	pull()
Y	mutate() transmute()
Y	summarise() summarize()
N	group_by() ungroup()
N	distinct()
N	do()
N	sample_n() sample_frac()
N	slice()
Y	tally() count() add_tally() add_count()
Y	top_n()
N	arrange_all() arrange_at() arrange_if()
N	filter_all() filter_if() filter_at()
N	group_by_all() group_by_at() group_by_if()
N	select_all() rename_all() select_if() rename_if() select_at() rename_at()
N	summarise_all() summarise_if() summarise_at() summarize_all() summarize_if() summarize_at() mutate_all() mu
N	all_vars() any_vars()
N	vars()
N	funs()
N	all_equal() all.equal(<tbl_df>)
N	bind_rows() bind_cols() combine()
N	intersect() union() union_all() setdiff() setequal()
N	inner_join() left_join() right_join() full_join() semi_join() anti_join()
N	inner_join(<tbl_df>) left_join(<tbl_df>) right_join(<tbl_df>) full_join(<tbl_df>) semi_join(<tbl_df>) anti_j
N	auto_copy()
N	compute() collect() collapse()
N	copy_to()
N	ident()
N	explain() show_query()
N	tbl() is.tbl() as.tbl()
N	src_mysql() src_postgres() src_sqlite()
N	sql()
N	groups() group_vars()
N	between()
N	case_when()
N	coalesce()
N	cumall() cumany() cummean()
N	desc()
N	if_else()
N	lead() lag()
N	order_by()
N	n()
N	n_distinct()
N	na_if()
N	near()
N	nth() first() last()
N	row_number() ntile() min_rank() dense_rank() percent_rank() cume_dist()
N	recode() recode_factor()
N	band_members band_instruments band_instruments2
N	nasa
N	starwars
N	storms
N	tbl_cube()
N	as.table(<tbl_cube>) as.data.frame(<tbl_cube>) as_data_frame(<tbl_cube>)
N	as_tbl_cube()

Chapter 10

Joins and complex queries (13)

Verify Docker is up and running:

```
sp_check_that_docker_is_up()
```

```
## [1] "Docker is up but running no containers"
```

verify pet DB is available, it may be stopped.

```
sp_show_all_docker_containers()
```

```
## [1] "CONTAINER ID        IMAGE               COMMAND                  CREATED             STATUS                    PORTS
## [2] "3fea949dfb09        postgres-dvdrental  \"docker-entrypoint.s…\"   21 seconds ago      Exited (0) 2 seco
```

Start up the `docker-pet` container

```
sp_docker_start("sql-pet")
```

now connect to the database with R

```
# need to wait for Docker & Postgres to come up before connecting.

con <- sp_get_postgres_connection(
  user = Sys.getenv("DEFAULT_POSTGRES_USER_NAME"),
  password = Sys.getenv("DEFAULT_POSTGRES_PASSWORD"),
  dbname = "dvdrental",
  seconds_to_test = 10
)
```

10.1 Database constraints

As a data analyst, you really do not have to worry about database constraints since you are primarily writing dplyr/SQL queries to pull data out of the database. Constraints can be enforced at multiple levels, column, table, multiple tables, or at the schema itself.

For this tutorial, we are primarily concerned with primary and foreign key constraints. If one looks at all the tables in the DVD Rental ERD, the first column is the name of the table followed by "id". This is the primary key on the table. In some of the tables, there are other columns that begin with the name of a different table, the foreign table, and end in "_id". These are foreign keys and the foreign key value is the primary key value on the foreign table. The DBA will index the primary and foreign key columns to speed up query performanace.

10.2 Making up data for Join Examples

10.2.1 insert yourself as a new customer

```
# Customer 600 should be the next customer.
# It gets deleted here just in case it was added in a different session.
dbExecute(
  con,
  "delete from customer
   where customer_id = 600;
  "
)
```

```
## [1] 0
```

```
# Now add yourself as the next customer.  Replace Sophie Yang with your name.
dbExecute(
  con,
  "insert into customer
  (customer_id,store_id,first_name,last_name,email,address_id
  ,activebool,create_date,last_update,active)
  values(600,2,'Sophie','Yang','email@email.com',1,TRUE,now()::date,now()::date,1)
  ;
  "
)
```

```
## [1] 1
```

The `film` table has a primary key, film_id, and a foreign key column, language_id. One cannot insert a new row into the film table with a language_id = 10 because of a constraint on the language_id column. The language_id value must already exist in the `language` table before the database will allow the new row to be inserted into the table.

To work around this inconvenience for the tutorial:

1. we drop the smy_film table if it exists from a previous session.

```
dbExecute(con, "drop table if exists smy_film;")
```

```
## [1] 0
```

2. we create a new table smy_film from the film table and add a new row with a language_id = 10;

```
dbExecute(con, "create table smy_film as select * from film;")
```

```
## [1] 1000
```

3. We create a film with language_id = 10;

```
dbExecute(
  con,
  "insert into smy_film
  (film_id,title,description,release_year,language_id
  ,rental_duration,rental_rate,length,replacement_cost,rating
   ,last_update,special_features,fulltext)
  values(1001,'Sophie''s Choice','orphaned language_id=10',2018,10
        ,7,4.99,120,14.99,'PG'
        ,now()::date,'{Trailers}','')
  ;
```

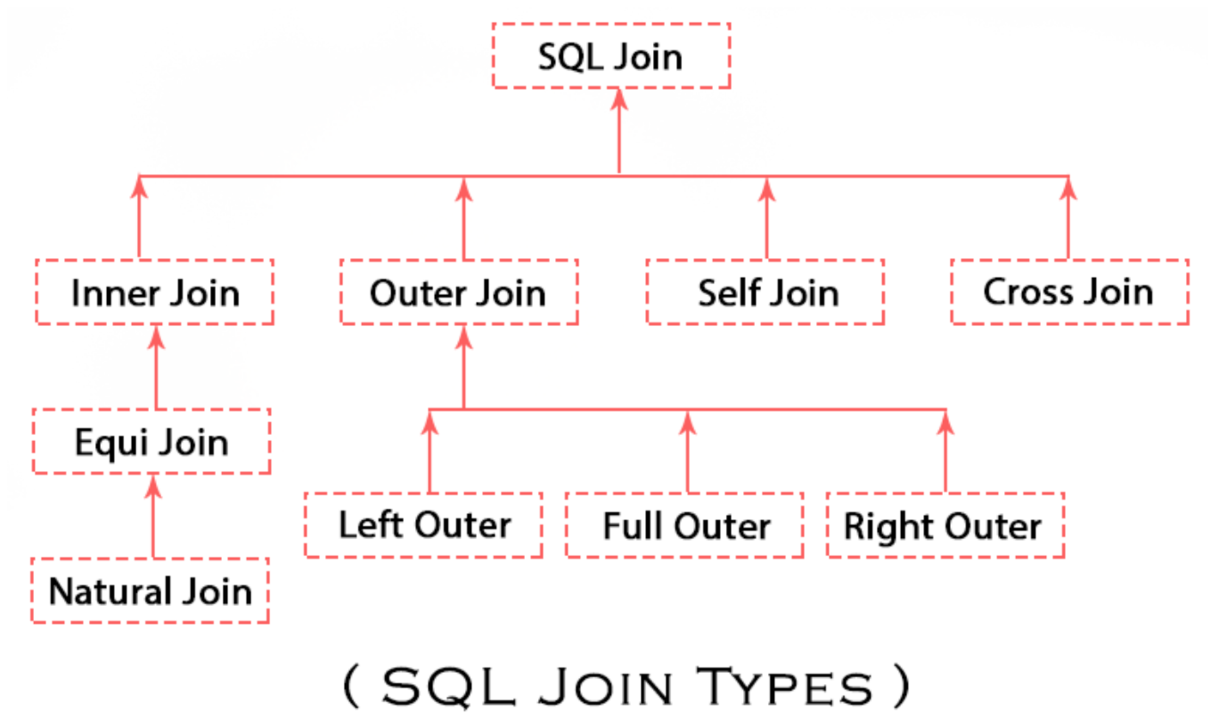


Figure 10.1: SQL_JOIN_TYPES

```
  "
)
```

```
## [1] 1
```

4. Confirm that the new record exists.

```
dbGetQuery(
  con,
  "select film_id,title,description,language_id from smy_film where film_id = 1001;"
)
```

```
##   film_id           title             description language_id
## 1    1001 Sophie's Choice orphaned language_id=10          10
```

10.3 Joins

In section 'SQL Quick Start Simple Retrieval', there is a brief discussion of databases and 3NF. The goal of normalization is to push the data into separate tables at a very granular level.

Bill Kent famously summarized 3NF as every non-key column "must provide a fact about the key,the whole key, and nothing but the key, so help me Codd."

Normalization breaks data down and JOINs denormalizes the data and builds it back up.

The above diagram can be found here There are additional graphics at the link, but the explanations are poorly worded and hard to follow.

The diagram above shows nicely the hierarchy of different types of joins. For this tutorial, we can think of joins as either an Inner Join or an Outer Join.

Instead of showing standard Venn diagrams showing the different JOINS, we use an analogy. For those interested though, the typical Venn diagrams can be found here.

10.3.1 Valentines Party

Imagine you are at a large costume Valentine's Day dance party. The hostess of the party, a data scientist, would like to learn more about the people attending her party. She interrupts the music to let everyone know it is time for the judges to evaluate the winners for best costumes and associated prizes.

She requests the following:

1. All the couples at the party to line up in front of her with the men on the left and the women on the right, (inner join)
2. All the remaining men to form a second line two feet behind the married men,(left outer join)
3. Right Outer Join: All the remaining women to form a third line two feet in front of the married women, (right outer join, all couples + unattached women)

Full Outer Join – As our data scientist looks out at the three lines, she can clearly see the three distinct lines, her full outer join.

As the three judges start walking down the lines, she makes one more announcement.

4. There is a special prize for the man and woman who can guess the average age of the members of the opposite sex. To give everyone a chance to come up with an average age, she asks the men to stay in line and the women to move down the mens line in order circling back around until they get back to their starting point in line, (full outer join, every man seen by every woman and vice versa).

It is hard enough to tell someone's age when they don't have a mask, how do you get the average age when people have masks?

The hostess knows that there is usually some data anomolies. As she looks out she sees a small cluster of people who did not line up. Being the hostess with the mostest, she wants to get to know that small cluster better. Since they are far off and in costume, she cannot tell if they are men or women. More importantly, she does not know if they identify as a man or a woman, both – (kind of a stretch for a self join), neither, or something else. Ahh, the inquisitive mind wants to know.

10.3.2 Join Syntax

Join	dplyr	sql
inner	inner_join(customer_tbl, rental_tbl, by = 'customer_id', suffix = c(".c", ".r")) customer_tbl %>% inner_join(rental_tbl, by = 'customer_id', suffix = c(".c", ".r"))	from customer c join rental r on c.customer_id = r.customer_id
left	left_join(customer_tbl, rental_tbl, by = 'customer_id', suffix = c(".c", ".r")) customer_tbl %>% left_join(rental_tbl, by = 'customer_id', suffix = c(".c", ".r"))	from customer c left outer join rental r on c.customer_id = r.customer_id
right	right_join(customer_tbl, rental_tbl, by = 'customer_id', suffix = c(".c", ".r")) customer_tbl %>% right_join(rental_tbl, by = 'customer_id', suffix = c(".c", ".r"))	from customer c right outer join rental r on c.customer_id = r.customer_id
full	full_join(customer_tbl, rental_tbl, by = 'customer_id', suffix = c(".c", ".r"))	from customer c full outer join rental r on c.customer_id = r.customer_id

Join	dplyr	sql
	customer_tbl %>% full_join(rental_tbl, by = 'customer_id', suffix = c(".c", ".r"))	

10.3.3 Join Tables

The dplyr join documentation describes two different types of joins, `mutating` and `filtering` joins. For those coming to R with a SQL background, the mutating documentation is misleading in one respect. Here is the inner_join documentation.

`inner_join()`

`return all rows from x where there are matching values in y, and all columns from x and y. If there are multipl`

The misleading part is that all the columns from *x* and *y*. If the join column is `KEY`, SQL will return x.KEY and y.KEY. Dplyr retuns KEY. It appears that the KEY value comes from the key/driving table. This difference should become clear in the outer join examples.

In the next couple of examples, we will pull all the language and smy_film table data from the database into memory because the tables are small. In the *_join verbs, the `by` and `suffix` parameters are included because it helps document the actual join and the source of join columns.

10.4 Natural Join Time Bomb

The dplyr default join is a natural join, joining tables on common column names. One of many links why one should not use natural joins can be found here.

10.5 Join Templates

In this section we look at two tables, `language` and `smy_film` and various joins using dplyr and SQL. Each dplyr code block has three purposes.

1. Show a working join example.

2. The code blocks can be used as templates for beginning more complex dplyr pipes.
3. The code blocks show the number of joins performed.

In these examples, the join condition, the `by` parameter,

`by = c('language_id','language_id')`

the two columns are the same. In multi-column joins, each language_id would be replace with a vector of column names used in the join by position. Note the column names do not need to be identical by position.

The suffix parameter is a way to distinguish the same column name in the joined tables. The suffixes are usually an single letter to represent the name of the table.

```
language_table <- DBI::dbReadTable(con, "language")
film_table <- DBI::dbReadTable(con, "smy_film")
```

10.5.1 dplyr Inner Join Template

```
languages_ij <- language_table %>%
  inner_join(film_table, by = c("language_id", "language_id"), suffix(c(".l", ".f"))) %>%
  group_by(language_id, name) %>%
  summarize(inner_joins = n())

languages_ij
```

```
## # A tibble: 1 x 3
## # Groups:   language_id [?]
##   language_id name                 inner_joins
##         <int> <chr>                      <int>
## 1           1 "English             "      1000
```

10.5.1.1 SQL Inner Join

```
rs <- dbGetQuery(
  con,
  "select l.language_id,l.name,count(*) n
   from language l join smy_film f on l.language_id = f.language_id
  group by l.language_id,l.name;"
)

rs
```

```
##   language_id                 name    n
## 1           1 English              1000
```

The output tells us that there are 1000 inner joins between the language_table and the film_table.

10.5.2 dplyr Left Outer Join Template

```
languages_loj <- language_table %>%
  left_join(film_table, by = c("language_id", "language_id"), suffix(c(".l", ".f"))) %>%
  mutate(
    join_type = "loj"
    , film_lang_id = if_else(is.na(film_id), film_id, language_id)
  ) %>%
  group_by(join_type, language_id, name, film_lang_id) %>%
  summarize(lojs = n()) %>%
  select(join_type, language_id, film_lang_id, name, lojs)
print(languages_loj)
```

```
## # A tibble: 6 x 5
## # Groups:   join_type, language_id, name [6]
##   join_type language_id film_lang_id name                  lojs
##   <chr>           <int>        <int> <chr>                <int>
## 1 loj                 1            1 "English             "  1000
## 2 loj                 2           NA "Italian             "     1
## 3 loj                 3           NA "Japanese            "     1
## 4 loj                 4           NA "Mandarin            "     1
## 5 loj                 5           NA "French              "     1
## 6 loj                 6           NA "German              "     1
```

```
# View(languages_loj)
# sp_print_df(languages_loj)
```

Compare the mutate verb in the above code block with film_lang_id in the equivalent SQL code block below.

10.5.2.1 SQL Left Outer Join

```
rs <- dbGetQuery(
  con,
  "select l.language_id
       ,f.language_id film_lang_id
       ,trim(l.name) as name
       ,count(*) lojs
   from language l left outer join smy_film f
        on l.language_id = f.language_id
  group by l.language_id,l.name,f.language_id
order by l.language_id;"
)
# sp_print_df(rs)
rs
```

```
##   language_id film_lang_id     name lojs
## 1           1            1  English 1000
## 2           2           NA  Italian    1
## 3           3           NA Japanese    1
## 4           4           NA Mandarin    1
## 5           5           NA   French    1
## 6           6           NA   German    1
```

The lojs column returns the number of rows found on the keys from the left table, language, and the right table, the film table. For the "English" row, the language_id and film_lang_id match and a 1000 inner joins were performed. For all the other languages, there was only 1 join and they all came from the left outer table, the language table, language_id's 2 - 6. The right table, the film table returned NA, because no match was found.

1. The left outer join always returns all rows from the left table, the driving/key table, if not reduced via a filter()/where clause.

2. All rows that inner join returns all the columns/derived columns specified in the select clause from both the left and right tables.

3. All rows from the left table, the outer table, without a matching row on the right returns all the columns/derived column values specified in the select clause from the left, but the values from right table have all values of NA.

10.5.2.2 dplyr Right Outer Join

```
languages_roj <- language_table %>%
  right_join(film_table, by = c("language_id", "language_id"), suffix(c(".l", ".f")), all = film_table)
  mutate(
    lang_id = if_else(is.na(name), 0L, language_id)
    , join_type = "rojs"
```

```
  ) %>%
  group_by(join_type, language_id, name, lang_id) %>%
  summarize(rojs = n()) %>%
  select(join_type, lang_id, language_id, name, rojs)

sp_print_df(languages_roj)
```

join_type	lang_id	language_id	name	rojs
rojs	1	1	English	1000
rojs	0	10	NA	1

```
languages_roj
```

```
## # A tibble: 2 x 5
## # Groups:   join_type, language_id, name [2]
##   join_type lang_id language_id name                      rojs
##   <chr>       <int>       <int> <chr>                    <int>
## 1 rojs            1           1 "English             "   1000
## 2 rojs            0          10 <NA>                         1
```

Review the mutate above with l.language_id below.

10.5.2.3 SQL Right Outer Join

```
rs <- dbGetQuery(
  con,
  "select 'roj' join_type,l.language_id,f.language_id language_id_f,l.name,count(*) rojs
   from language l right outer join smy_film f on l.language_id = f.language_id
  group by l.language_id,l.name,f.language_id
order by l.language_id;"
)
sp_print_df(rs)
```

join_type	language_id	language_id_f	name	rojs
roj	1	1	English	1000
roj	NA	10	NA	1

```
rs
```

```
##   join_type language_id language_id_f                 name rojs
## 1       roj           1             1 English              1000
## 2       roj          NA            10                 <NA>    1
```

The rojs column returns the number of rows found on the keys from the right table, film, and the left table, the language table. For the "English" row, the language_id and film_lang_id match and a 1000 inner joins were performed. For language_id = 10 from the right table, there was only 1 join to a non-existant row in the language table on the left.

1. The right outer join always returns all rows from the right table, the driving/key table, if not reduced via a filter()/where clause.

2. All rows that inner join returns all the columns/derived columns specified in the select clause from both the left and right tables.

3. All rows from the right table, the outer table, without a matching row on the left returns all the columns/derived column values specified in the select clause from the right, but the values from left table have all values of NA.

10.5.2.4 dplyr Full Outer Join

```
languages_foj <- language_table %>%
  full_join(film_table, by = c("language_id", "language_id"), suffix(c(".l", ".f"))) %>%
  mutate(film_lang = if_else(is.na(film_id), paste0("No ", name, " films."), if_else(is.na(name), "Alie
  group_by(language_id, name, film_lang) %>%
  summarize(n = n())

sp_print_df(languages_foj)
```

language_id	name	film_lang	n
1	English	English	1000
2	Italian	No Italian films.	1
3	Japanese	No Japanese films.	1
4	Mandarin	No Mandarin films.	1
5	French	No French films.	1
6	German	No German films.	1
10	NA	Alien	1

```
languages_foj
```

```
## # A tibble: 7 x 4
## # Groups:   language_id, name [?]
##   language_id name                    film_lang                         n
##         <int> <chr>                   <chr>                         <int>
## 1           1 "English              " "English              "        1000
## 2           2 "Italian              " No Italian             films.     1
## 3           3 "Japanese             " No Japanese            films.     1
## 4           4 "Mandarin             " No Mandarin            films.     1
## 5           5 "French               " No French              films.     1
## 6           6 "German               " No German              films.     1
## 7          10 <NA>                    Alien                             1
```

10.5.2.5 SQL full Outer Join

```
rs <- dbGetQuery(
  con,
  "select l.language_id,l.name,f.language_id language_id_f,count(*) fojs
   from language l full outer join smy_film f on l.language_id = f.language_id
  group by l.language_id,l.name,f.language_id
order by l.language_id;"
)
sp_print_df(rs)
```

language_id	name	language_id_f	fojs
1	English	1	1000
2	Italian	NA	1
3	Japanese	NA	1
4	Mandarin	NA	1
5	French	NA	1
6	German	NA	1
NA	NA	10	1

```
rs
```

```
##   language_id                 name language_id_f fojs
## 1           1 English                          1 1000
## 2           2 Italian                         NA    1
## 3           3 Japanese                        NA    1
## 4           4 Mandarin                        NA    1
## 5           5 French                          NA    1
## 6           6 German                          NA    1
## 7          NA                 <NA>            10    1
```

Looking at the SQL output, the full outer join is the combination of the left and right outer joins.

1. Language_id = 1 is the inner join.
2. Language_id = 2 - 6 is the left outer join
3. Language_id = 10 is the right outer join.

One can also just look at the language_id on the left and language_id_f on the right for a non NA value to see which side is outer side/driving side of the join.

10.5.2.6 dplyr anti Join

The anti join is a left outer join without the inner joined rows. It only returns the rows from the left table that do not have a match from the right table.

```
languages_aj <- language_table %>%
  anti_join(film_table, by = c("language_id", "language_id"), suffix(c(".l", ".f"))) %>%
  mutate(type = "anti_join") %>%
  group_by(type, language_id, name) %>%
  summarize(anti_joins = n()) %>%
  select(type, language_id, name, anti_joins)
sp_print_df(languages_aj)
```

type	language_id	name	anti_joins
anti_join	2	Italian	1
anti_join	3	Japanese	1
anti_join	4	Mandarin	1
anti_join	5	French	1
anti_join	6	German	1

```
languages_aj
```

```
## # A tibble: 5 x 4
## # Groups:   type, language_id [5]
##   type      language_id name                 anti_joins
##   <chr>           <int> <chr>                     <int>
## 1 anti_join           2 "Italian           "          1
## 2 anti_join           3 "Japanese          "          1
## 3 anti_join           4 "Mandarin          "          1
## 4 anti_join           5 "French            "          1
## 5 anti_join           6 "German            "          1
```

10.5.2.7 SQL anti Join 1, Left Outer Join where NULL on Right

SQL doesn't have an anti join key word. Here are three different ways to achieve the same result.

```
rs <- dbGetQuery(
  con,
  "select l.language_id,l.name,count(*) fojs
   from language l left outer join smy_film f on l.language_id = f.language_id
  where f.language_id is null
  group by l.language_id,l.name
order by l.language_id;"
)
sp_print_df(rs)
```

language_id	name	fojs
2	Italian	1
3	Japanese	1
4	Mandarin	1
5	French	1
6	German	1

```
rs
```

```
##   language_id                 name fojs
## 1           2 Italian                 1
## 2           3 Japanese                1
## 3           4 Mandarin                1
## 4           5 French                  1
## 5           6 German                  1
```

10.5.2.8 SQL anti Join 2, ID in driving table and NOT IN lookup table

```
rs <- dbGetQuery(
  con,
  "select l.language_id,l.name,count(*) fojs
   from language l
  where l.language_id NOT IN (select language_id from film)
  group by l.language_id,l.name
order by l.language_id;"
)
sp_print_df(rs)
```

language_id	name	fojs
2	Italian	1
3	Japanese	1
4	Mandarin	1
5	French	1
6	German	1

```
rs
```

```
##   language_id                 name fojs
## 1           2 Italian                 1
## 2           3 Japanese                1
## 3           4 Mandarin                1
## 4           5 French                  1
## 5           6 German                  1
```

10.5.2.9 SQL anti Join 3, NOT EXISTS and Correlated subquery

```
rs <- dbGetQuery(
  con,
  "select l.language_id,l.name,count(*) fojs
   from language l
  where not exists (select language_id from film f where f.language_id = l.language_id)
 group by l.language_id,l.name
"
)
sp_print_df(rs)
```

language_id	name	fojs
2	Italian	1
3	Japanese	1
4	Mandarin	1
5	French	1
6	German	1

```
rs
```

```
##   language_id                 name fojs
## 1           2 Italian                 1
## 2           3 Japanese                1
## 3           4 Mandarin                1
## 4           5 French                  1
## 5           6 German                  1
```

10.6 SQL anti join Costs

```
sql_aj1 <- dbGetQuery(
  con,
  "explain analyze select l.language_id,l.name,count(*) fojs
   from language l left outer join smy_film f on l.language_id = f.language_id
  where f.language_id is null
  group by l.language_id,l.name
"
)

sql_aj2 <- dbGetQuery(
  con,
  "explain analyze select l.language_id,l.name,count(*) fojs
   from language l
  where l.language_id NOT IN (select language_id from film)
  group by l.language_id,l.name
"
)

sql_aj3 <- dbGetQuery(
  con,
  "explain analyze select l.language_id,l.name,count(*) fojs
   from language l
  where not exists (select language_id from film f where f.language_id = l.language_id)
```

```
 group by l.language_id,l.name
"
)
```

10.6.0.0.1 SQL Costs

```
print(glue("sql_aj1 loj-null costs=", sql_aj1[1, 1]))
```

```
## sql_aj1 loj-null costs=GroupAggregate  (cost=68.56..68.61 rows=3 width=96) (actual time=18.605..18.727 r
```

```
print(glue("sql_aj2 not in costs=", sql_aj2[1, 1]))
```

```
## sql_aj2 not in costs=GroupAggregate  (cost=67.60..67.65 rows=3 width=96) (actual time=16.651..16.760 row
```

```
print(glue("sql_aj3 not exist costs=", sql_aj3[1, 1]))
```

```
## sql_aj3 not exist costs=GroupAggregate  (cost=24.24..24.30 rows=3 width=96) (actual time=0.379..0.480 ro
```

10.7 dplyr Anti joins

In this next section we look at two methods to implemnt an anti join in dplyr.

```
customer_table <- tbl(con, "customer") # DBI::dbReadTable(con, "customer")
rental_table <- tbl(con, "rental") # DBI::dbReadTable(con, "rental")

# Method 1.  dplyr anti_join
daj1 <-
  anti_join(customer_table, rental_table, by = "customer_id", suffix = c(".c", ".r")) %>%
  select(c("first_name", "last_name", "email")) %>%
  explain()
```

```
## <SQL>
## SELECT "first_name", "last_name", "email"
## FROM (SELECT * FROM "customer" AS "TBL_LEFT"
##
## WHERE NOT EXISTS (
##   SELECT 1 FROM "rental" AS "TBL_RIGHT"
##   WHERE ("TBL_LEFT"."customer_id" = "TBL_RIGHT"."customer_id")
## )) "lghnetfgzu"
```

```
##
```

```
## <PLAN>
## Hash Anti Join  (cost=510.99..552.63 rows=300 width=334)
##   Hash Cond: ("TBL_LEFT".customer_id = "TBL_RIGHT".customer_id)
##   ->  Seq Scan on customer "TBL_LEFT"  (cost=0.00..14.99 rows=599 width=338)
##   ->  Hash  (cost=310.44..310.44 rows=16044 width=2)
##         ->  Seq Scan on rental "TBL_RIGHT"  (cost=0.00..310.44 rows=16044 width=2)
```

```
customer_table <- tbl(con, "customer") # DBI::dbReadTable(con, "customer")
rental_table <- tbl(con, "rental") # DBI::dbReadTable(con, "rental")

# Method 2.  dplyr loj with NA
daj2 <-
  left_join(customer_table, rental_table, by = c("customer_id", "customer_id"), suffix = c(".c", ".r"))
  filter(is.na(rental_id)) %>%
```

```r
  select(c("first_name", "last_name", "email")) %>%
  explain()
```

```
## <SQL>
## SELECT "first_name", "last_name", "email"
## FROM (SELECT "TBL_LEFT"."customer_id" AS "customer_id", "TBL_LEFT"."store_id" AS "store_id", "TBL_LEFT"
##   FROM "customer" AS "TBL_LEFT"
##   LEFT JOIN "rental" AS "TBL_RIGHT"
##   ON ("TBL_LEFT"."customer_id" = "TBL_RIGHT"."customer_id")
## ) "bisndnmtew"
## WHERE ((("rental_id") IS NULL))

##

## <PLAN>
## Hash Right Join  (cost=22.48..375.33 rows=80 width=334)
##   Hash Cond: ("TBL_RIGHT".customer_id = "TBL_LEFT".customer_id)
##   Filter: ("TBL_RIGHT".rental_id IS NULL)
##   ->  Seq Scan on rental "TBL_RIGHT"  (cost=0.00..310.44 rows=16044 width=6)
##   ->  Hash  (cost=14.99..14.99 rows=599 width=338)
##         ->  Seq Scan on customer "TBL_LEFT"  (cost=0.00..14.99 rows=599 width=338)
```

10.7.1 dplyr Costs

```
<PLAN>
Hash Anti Join  (cost=510.99..529.72 rows=1 width=45)
  Hash Cond: ("TBL_LEFT".customer_id = "TBL_RIGHT".customer_id)
  ->  Seq Scan on customer "TBL_LEFT"  (cost=0.00..14.99 rows=599 width=49)
  ->  Hash  (cost=310.44..310.44 rows=16044 width=2)
        ->  Seq Scan on rental "TBL_RIGHT"  (cost=0.00..310.44 rows=16044 width=2)

<PLAN>
Hash Right Join  (cost=22.48..375.33 rows=1 width=45)
  Hash Cond: ("TBL_RIGHT".customer_id = "TBL_LEFT".customer_id)
  Filter: ("TBL_RIGHT".rental_id IS NULL)
  ->  Seq Scan on rental "TBL_RIGHT"  (cost=0.00..310.44 rows=16044 width=6)
  ->  Hash  (cost=14.99..14.99 rows=599 width=49)
        ->  Seq Scan on customer "TBL_LEFT"  (cost=0.00..14.99 rows=599 width=49)
```

In this example, the dplyr anti_join verb is *1.4113447 to 22.7308719* times more expensive than the left outer join with a null condition.

```r
sql_aj1 <- dbGetQuery(
  con,
  "explain analyze select c.customer_id,count(*) lojs
   from customer c left outer join rental r on c.customer_id = r.customer_id
  where r.customer_id is null
  group by c.customer_id
order by c.customer_id;"
)
sp_print_df(sql_aj1)
```

QUERY PLAN
GroupAggregate (cost=564.97..570.22 rows=300 width=12) (actual time=265.543..265.556 rows=1 loops=1)
Group Key: c.customer_id
-> Sort (cost=564.97..565.72 rows=300 width=4) (actual time=265.511..265.525 rows=1 loops=1)
Sort Key: c.customer_id
Sort Method: quicksort Memory: 25kB
-> Hash Anti Join (cost=510.99..552.63 rows=300 width=4) (actual time=265.456..265.483 rows=1 loops=1)
Hash Cond: (c.customer_id = r.customer_id)
-> Seq Scan on customer c (cost=0.00..14.99 rows=599 width=4) (actual time=0.036..4.750 rows=600 loops=1)
-> Hash (cost=310.44..310.44 rows=16044 width=2) (actual time=255.947..255.954 rows=16044 loops=1)
Buckets: 16384 Batches: 1 Memory Usage: 661kB
-> Seq Scan on rental r (cost=0.00..310.44 rows=16044 width=2) (actual time=0.035..127.540 rows=16044 loops=1)
Planning time: 0.175 ms
Execution time: 265.752 ms

```
sql_aj1
```

```
##                                                                                          QUERY PLAN
## 1                         GroupAggregate  (cost=564.97..570.22 rows=300 width=12) (actual time=265.543..26
## 2                                                                                   Group Key: c.customer_id
## 3                              ->  Sort  (cost=564.97..565.72 rows=300 width=4) (actual time=265.511..265.5
## 4                                                                                    Sort Key: c.customer_id
## 5                                                                           Sort Method: quicksort  Memory: 25kB
## 6                        ->  Hash Anti Join  (cost=510.99..552.63 rows=300 width=4) (actual time=265.456..26
## 7                                                                       Hash Cond: (c.customer_id = r.customer_i
## 8                      ->  Seq Scan on customer c  (cost=0.00..14.99 rows=599 width=4) (actual time=0.036..4.
## 9                           ->  Hash  (cost=310.44..310.44 rows=16044 width=2) (actual time=255.947..255.954
## 10                                                                   Buckets: 16384  Batches: 1  Memory Usage: 66
## 11                  ->  Seq Scan on rental r  (cost=0.00..310.44 rows=16044 width=2) (actual time=0.035..127.
## 12                                                                                   Planning time: 0.175 ms
## 13                                                                                 Execution time: 265.752 ms
```

```
sql_aj3 <- dbGetQuery(
  con,
  "explain analyze
select c.customer_id,count(*) lojs
   from customer c
  where not exists (select customer_id from rental r where c.customer_id = r.customer_id)
 group by c.customer_id
"
)

print(glue("sql_aj1 loj-null costs=", sql_aj1[1, 1]))
```

```
## sql_aj1 loj-null costs=GroupAggregate  (cost=564.97..570.22 rows=300 width=12) (actual time=265.543..265
```

```
print(glue("sql_aj3 not exist costs=", sql_aj3[1, 1]))
```

```
## sql_aj3 not exist costs=HashAggregate  (cost=554.13..557.13 rows=300 width=12) (actual time=252.234..252
```

10.8 Exercises

10.8.1 Anti joins – Find customers who have never rented a movie, take 2.

This is a left outer join from customer to the rental table with an NA rental_id.

10.8.1.1 SQL Anti-Join

```
rs <- dbGetQuery(
  con,
  "select c.first_name
                      ,c.last_name
                      ,c.email
                  from customer c
                       left outer join rental r
                            on c.customer_id = r.customer_id
                 where r.rental_id is null;
               "
)
sp_print_df(head(rs))
```

first_name	last_name	email
Sophie	Yang	email@email.com

<– Add dplyr semi-join example –>

10.8.2 SQL Rows Per Table

In the examples above, we looked at how many rows were involved in each of the join examples and which side of the join they came from. It is often helpful to know how many rows are in each table as a sanity check on the joins.

Below is the SQL version to return all the row counts from each table in the DVD Rental System.

```
rs <- dbGetQuery(
  con,
  "select *
               from (      select 'actor' tbl_name,count(*) from actor
                     union select 'category' tbl_name,count(*) from category
                     union select 'film' tbl_name,count(*) from film
                     union select 'film_actor' tbl_name,count(*) from film_actor
                     union select 'film_category' tbl_name,count(*) from film_category
                     union select 'language' tbl_name,count(*) from language
                     union select 'inventory' tbl_name,count(*) from inventory
                     union select 'rental' tbl_name,count(*) from rental
                     union select 'payment' tbl_name,count(*) from payment
                     union select 'staff' tbl_name,count(*) from staff
                     union select 'customer' tbl_name,count(*) from customer
                     union select 'address' tbl_name,count(*) from address
                     union select 'city' tbl_name,count(*) from city
                     union select 'country' tbl_name,count(*) from country
                     union select 'store' tbl_name,count(*) from store
                     union select 'smy_film' tbl_name,count(*) from smy_film
                     ) counts
                order by tbl_name
               ;
              "
)
sp_print_df(head(rs))
```

tbl_name	count
actor	200
address	603
category	16
city	600
country	109
customer	600

```
rs
```

```
##         tbl_name count
## 1          actor   200
## 2        address   603
## 3       category    16
## 4           city   600
## 5        country   109
## 6       customer   600
## 7           film  1000
## 8     film_actor  5462
## 9  film_category  1000
## 10     inventory  4581
## 11      language     6
## 12       payment 14596
## 13        rental 16044
## 14      smy_film  1001
## 15         staff     2
## 16         store     2
```

10.8.2.1 Exercise dplyr Rows Per Table

In the code block below

1. Get the row counts for a couple more tables
2. What is the structure of film_table object?

```
film_table <- tbl(con, "film") # DBI::dbReadTable(con, "customer")
language_table <- tbl(con, "language") # DBI::dbReadTable(con, "rental")

film_rows <- film_table %>% mutate(name = "film") %>% group_by(name) %>% summarize(rows = n())
language_rows <- language_table %>%
  mutate(name = "language") %>%
  group_by(name) %>%
  summarize(rows = n())
rows_per_table <- rbind(as.data.frame(film_rows), as.data.frame(language_rows))
rows_per_table
```

```
##       name rows
## 1     film 1000
## 2 language    6
```

10.8.2.2 SQL film distribution based on language

The SQL below is very similar to the `SQL full Outer Join` above. Instead of counting the joins, it counts the number films associated with each language.

```
rs <- dbGetQuery(
  con,
  "select l.language_id id
                       ,l.name
                       ,sum(case when f.language_id is not null then 1 else 0 end) total
                   from language l
                        full outer join film f
                             on l.language_id = f.language_id
                  group by l.language_id,l.name
                  order by l.name;
                 ;
                "
)
sp_print_df(head(rs))
```

id	name	total
1	English	1000
5	French	0
6	German	0
2	Italian	0
3	Japanese	0
4	Mandarin	0

```
rs
```

```
##   id                 name total
## 1  1 English              1000
## 2  5 French                  0
## 3  6 German                  0
## 4  2 Italian                 0
## 5  3 Japanese                0
## 6  4 Mandarin                0
```

10.8.2.3 Exercise dplyr film distribution based on language

Below is the code block from the `dplyr Full Outer Join` section above. Modify the code block to match the output from the SQL version.

```
rs <- dbGetQuery(
  con,
  "select l.language_id,l.name,f.language_id language_id_f,count(*) fojs
   from language l full outer join smy_film f on l.language_id = f.language_id
  group by l.language_id,l.name,f.language_id
order by l.language_id;"
)
sp_print_df(rs)
```

language_id	name	language_id_f	fojs
1	English	1	1000
2	Italian	NA	1
3	Japanese	NA	1
4	Mandarin	NA	1
5	French	NA	1
6	German	NA	1
NA	NA	10	1

```
rs
```

```
##   language_id                 name language_id_f fojs
## 1           1 English                         1 1000
## 2           2 Italian                        NA    1
## 3           3 Japanese                       NA    1
## 4           4 Mandarin                       NA    1
## 5           5 French                         NA    1
## 6           6 German                         NA    1
## 7          NA                 <NA>           10    1
```

10.9 Store analysis

How are the stores performing.

10.9.1 SQL store revenue stream

How are the stores performing? The SQL code shows the payments made to each store in the business.

```
rs <- dbGetQuery(
  con,
  "select store_id,sum(p.amount) amt,count(*) cnt
                 from payment p
                      join staff s
                        on p.staff_id = s.staff_id
               group by store_id order by 2 desc
               ;
              "
)
sp_print_df(head(rs))
```

store_id	amt	cnt
2	31059.92	7304
1	30252.12	7292

10.9.1.1 Exercise dplyr store revenue stream

Complete the following code block to return the payments made to each store.

```
payment_table <- tbl(con, "payment") # DBI::dbReadTable(con, "payment")
staff_table <- tbl(con, "staff") # DBI::dbReadTable(con, "staff")

store_revenue <- payment_table %>%
  inner_join(staff_table, by = "staff_id", suffix = c(".p", ".s")) %>%
  head()

store_revenue
```

```
## # Source:   lazy query [?? x 16]
## # Database: postgres [postgres@localhost:5432/dvdrental]
##   payment_id customer_id staff_id rental_id amount payment_date
##        <int>       <int>    <int>     <int>  <dbl> <dttm>
## 1      17503         341        2      1520   7.99 2007-02-15 22:25:46
```

```
## 2      17504         341         1       1778   1.99 2007-02-16 17:23:14
## 3      17505         341         1       1849   7.99 2007-02-16 22:41:45
## 4      17506         341         2       2829   2.99 2007-02-19 19:39:56
## 5      17507         341         2       3130   7.99 2007-02-20 17:31:48
## 6      17508         341         1       3382   5.99 2007-02-21 12:33:49
## # ... with 10 more variables: first_name <chr>, last_name <chr>,
## #   address_id <int>, email <chr>, store_id <int>, active <lgl>,
## #   username <chr>, password <chr>, last_update <dttm>, picture <blob>
```

10.9.2 SQL:Estimate Outstanding Balance

The following SQL code calculates for each store

1. the number of payments still open and closed from the DVD Rental Stores customer base.
2. the total amount that their customers have paid
3. the average price per/movie based off of the movies that have been paid.
4. the estimated outstanding balance based off the open unpaid rentals * the average price per paid movie.

```
rs <- dbGetQuery(
  con,
  "SELECT s.store_id store,sum(CASE WHEN payment_id IS NULL THEN 1 ELSE 0 END) open
    ,sum(CASE WHEN payment_id IS NOT NULL THEN 1 ELSE 0 END) paid
    ,sum(p.amount) paid_amt
    ,count(*) rentals
    ,round(sum(p.amount) / sum(CASE WHEN payment_id IS NOT NULL
                                THEN 1
                                ELSE 0
                           END), 2) avg_price
    ,round(round(sum(p.amount) / sum(CASE WHEN payment_id IS NOT NULL
                                      THEN 1
                                      ELSE 0
                                 END), 2) * sum(CASE WHEN payment_id IS NULL
                                                     THEN 1
                                                     ELSE 0
                                                END), 2) est_balance
FROM rental r
LEFT JOIN payment p
    ON r.rental_id = p.rental_id
JOIN staff s
    ON r.staff_id = s.staff_id
group by s.store_id;
"
)
sp_print_df(head(rs))
```

store	open	paid	paid_amt	rentals	avg_price	est_balance
1	713	7331	30498.71	8044	4.16	2966.08
2	739	7265	30813.33	8004	4.24	3133.36

```
rs
```

```
##   store open paid paid_amt rentals avg_price est_balance
## 1     1  713 7331 30498.71    8044      4.16     2966.08
## 2     2  739 7265 30813.33    8004      4.24     3133.36
```

10.9.2.1 Exercise Dplyr Modify the following dplyr code to match the SQL output from above.

```
payment_table <- tbl(con, "payment") # DBI::dbReadTable(con, "payment")
rental_table <- tbl(con, "rental") # DBI::dbReadTable(con, "rental")

est_bal <- rental_table %>%
  left_join(payment_table, by = c("rental_id", "rental_id"), suffix = c(".r", ".p")) %>%
  mutate(
    missing = ifelse(is.na(payment_id), 1, 0)
    , found = ifelse(!is.na(payment_id), 1, 0)
  ) %>%
  summarize(
    open = sum(missing, na.rm = TRUE)
    , paid = sum(found, na.rm = TRUE)
    , paid_amt = sum(amount, na.rm = TRUE)
    , rentals = n()
  ) %>%
  summarize(
    open = open
    , paid = paid
    , paid_amt = paid_amt
    , rentals = rentals
    , avg_price = paid_amt / paid
    , est_balance = paid_amt / paid * open
  )
est_bal
```

```
## # Source:   lazy query [?? x 6]
## # Database: postgres [postgres@localhost:5432/dvdrental]
##    open  paid paid_amt rentals         avg_price est_balance
##   <dbl> <dbl>    <dbl> <S3: integer64>     <dbl>       <dbl>
## 1  1452 14596   61312. 16048                4.20       6099.
```

10.9.3 SQL actual outstanding balance

In the previous exercise, we estimated the outstanding amount. After reviewing the rental table, the actual movie rental rate is in the table. We use that to calculate the outstanding balance below.

```
rs <- dbGetQuery(
  con,
  "SELECT sum(f.rental_rate) open_amt
    ,count(*) count
FROM rental r
LEFT JOIN payment p
    ON r.rental_id = p.rental_id
INNER JOIN inventory i
    ON r.inventory_id = i.inventory_id
INNER JOIN film f
    ON i.film_id = f.film_id
WHERE p.rental_id IS NULL
;"
)
sp_print_df(head(rs))
```

open_amt	count
4297.48	1452

```
rs
```

```
##   open_amt count
## 1  4297.48  1452
```

```
payment_table <- tbl(con, "payment") # DBI::dbReadTable(con, "payment")
rental_table <- tbl(con, "rental") # DBI::dbReadTable(con, "rental")
inventory_table <- tbl(con, "inventory") # DBI::dbReadTable(con, "inventory")
film_table <- tbl(con, "film") # DBI::dbReadTable(con, "film")

act_bal <- rental_table %>%
  left_join(payment_table, by = c("rental_id", "rental_id"), suffix = c(".r", ".p")) %>%
  inner_join(inventory_table, by = c("inventory_id", "inventory_id"), suffix = c(".r", ".i")) %>%
  inner_join(film_table, by = c("film_id", "film_id"), suffix = c(".i", ".f")) %>%
  head()

act_bal
```

```
## # Source:   lazy query [?? x 27]
## # Database: postgres [postgres@localhost:5432/dvdrental]
##   rental_id rental_date         inventory_id customer_id.r
##       <int> <dttm>                     <int>         <int>
## 1         1 2005-05-24 22:53:30          367           130
## 2         2 2005-05-24 22:54:33         1525           459
## 3         3 2005-05-24 23:03:39         1711           408
## 4         4 2005-05-24 23:04:41         2452           333
## 5         5 2005-05-24 23:05:21         2079           222
## 6         6 2005-05-24 23:08:07         2792           549
## # ... with 23 more variables: return_date <dttm>, staff_id.r <int>,
## #   last_update.r <dttm>, payment_id <int>, customer_id.p <int>,
## #   staff_id.p <int>, amount <dbl>, payment_date <dttm>, film_id <int>,
## #   store_id <int>, last_update.i <dttm>, title <chr>, description <chr>,
## #   release_year <int>, language_id <int>, rental_duration <int>,
## #   rental_rate <dbl>, length <int>, replacement_cost <dbl>, rating <S3:
## #   pq_mpaa_rating>, last_update <dttm>, special_features <S3: pq__text>,
## #   fulltext <S3: pq_tsvector>
```

10.9.4 Rank customers with highest open amounts

```
rs <- dbGetQuery(
  con,
  "select c.customer_id,c.first_name,c.last_name,sum(f.rental_rate) open_amt,count(*) count
                 from rental r
                      left outer join payment p
                        on r.rental_id = p.rental_id
                      join inventory i
                        on r.inventory_id = i.inventory_id
                      join film f
                        on i.film_id = f.film_id
                      join customer c
                        on r.customer_id = c.customer_id
                where p.rental_id is null
```

```
                        group by c.customer_id,c.first_name,c.last_name
                        order by open_amt desc
                        limit 25
                       ;"
)
sp_print_df(head(rs))
```

customer_id	first_name	last_name	open_amt	count
293	Mae	Fletcher	35.90	10
307	Joseph	Joy	31.90	10
316	Steven	Curley	31.90	10
299	James	Gannon	30.91	9
274	Naomi	Jennings	29.92	8
326	Jose	Andrew	28.93	7

```
rs
```

```
##    customer_id first_name   last_name open_amt count
## 1          293        Mae    Fletcher    35.90    10
## 2          307     Joseph         Joy    31.90    10
## 3          316     Steven      Curley    31.90    10
## 4          299      James      Gannon    30.91     9
## 5          274      Naomi    Jennings    29.92     8
## 6          326       Jose      Andrew    28.93     7
## 7          338     Dennis      Gilman    27.92     8
## 8          277       Olga     Jimenez    27.92     8
## 9          327      Larry    Thrasher    26.93     7
## 10         330      Scott     Shelley    26.93     7
## 11         322      Jason   Morrissey    26.91     9
## 12         340    Patrick      Newsom    25.92     8
## 13         336     Joshua        Mark    25.92     8
## 14         304      David       Royal    24.93     7
## 15         339     Walter    Perryman    23.94     6
## 16         239     Minnie      Romero    23.94     6
## 17         310     Daniel      Cabral    22.93     7
## 18         296     Ramona        Hale    22.93     7
## 19         313     Donald       Mahon    22.93     7
## 20         287      Becky       Miles    22.93     7
## 21         272        Kay    Caldwell    22.93     7
## 22         303    William Satterfield    22.93     7
## 23         329      Frank    Waggoner    22.91     9
## 24         311       Paul       Trout    21.92     8
## 25         109       Edna        West    20.93     7
```

10.9.5 what film has been rented the most

```
rs <- dbGetQuery(
  con,
  "SELECT i.film_id
    ,f.title
    ,rental_rate
    ,sum(rental_rate) revenue
    ,count(*) count --16044
FROM rental r
```

```
INNER JOIN inventory i
    ON r.inventory_id = i.inventory_id
INNER JOIN film f
    ON i.film_id = f.film_id
GROUP BY i.film_id
    ,f.title
    ,rental_rate
ORDER BY count DESC
LIMIT 25
;"
)
sp_print_df(head(rs))
```

film_id	title	rental_rate	revenue	count
103	Bucket Brotherhood	4.99	169.66	34
738	Rocketeer Mother	0.99	32.67	33
489	Juggler Hardly	0.99	31.68	32
730	Ridgemont Submarine	0.99	31.68	32
767	Scalawag Duck	4.99	159.68	32
331	Forward Temple	2.99	95.68	32

```
rs
```

```
##    film_id               title rental_rate revenue count
## 1      103  Bucket Brotherhood        4.99  169.66    34
## 2      738    Rocketeer Mother        0.99   32.67    33
## 3      489      Juggler Hardly        0.99   31.68    32
## 4      730 Ridgemont Submarine        0.99   31.68    32
## 5      767       Scalawag Duck        4.99  159.68    32
## 6      331      Forward Temple        2.99   95.68    32
## 7      382      Grit Clockwork        0.99   31.68    32
## 8      735        Robbers Joon        2.99   92.69    31
## 9      973           Wife Turn        4.99  154.69    31
## 10     621        Network Peak        2.99   92.69    31
## 11    1000           Zorro Ark        4.99  154.69    31
## 12      31       Apache Divine        4.99  154.69    31
## 13     369   Goodfellas Salute        4.99  154.69    31
## 14     753     Rush Goodfellas        0.99   30.69    31
## 15     891      Timberland Sky        0.99   30.69    31
## 16     418         Hobbit Alien        0.99   30.69    31
## 17     127       Cat Coneheads        4.99  149.70    30
## 18     559          Married Go        2.99   89.70    30
## 19     374       Graffiti Love        0.99   29.70    30
## 20     748 Rugrats Shakespeare        0.99   29.70    30
## 21     239        Dogma Family        4.99  149.70    30
## 22     285     English Bulworth        0.99   29.70    30
## 23     109  Butterfly Chocolat        0.99   29.70    30
## 24     450     Idols Snatchers        2.99   89.70    30
## 25     609       Muscle Bright        2.99   89.70    30
```

10.9.6 what film has been generated the most revenue assuming all amounts are collected

```
rs <- dbGetQuery(
  con,
  "select i.film_id,f.title,rental_rate
                     ,sum(rental_rate) revenue,count(*) count  --16044
                 from rental r
                      join inventory i
                        on r.inventory_id = i.inventory_id
                      join film f
                        on i.film_id = f.film_id
               group by i.film_id,f.title,rental_rate
               order by revenue desc
               ;"
)
sp_print_df(head(rs))
```

film_id	title	rental_rate	revenue	count
103	Bucket Brotherhood	4.99	169.66	34
767	Scalawag Duck	4.99	159.68	32
973	Wife Turn	4.99	154.69	31
31	Apache Divine	4.99	154.69	31
369	Goodfellas Salute	4.99	154.69	31
1000	Zorro Ark	4.99	154.69	31

10.9.7 which films are in one store but not the other.

```
rs <- dbGetQuery(
  con,
  "select coalesce(i1.film_id,i2.film_id) film_id
                     ,f.title,f.rental_rate,i1.store_id,i1.count,i2.store_id,i2.count
                 from     (select film_id,store_id,count(*) count
                              from inventory where store_id = 1
                            group by film_id,store_id) as i1
                        full outer join
                           (select film_id,store_id,count(*) count
                              from inventory where store_id = 2
                            group by film_id,store_id
                           ) as i2
                          on i1.film_id = i2.film_id
                        join film f
                          on coalesce(i1.film_id,i2.film_id) = f.film_id
                where i1.film_id is null or i2.film_id is null
               order by f.title  ;
             "
)
sp_print_df(head(rs))
```

film_id	title	rental_rate	store_id	count	store_id..6	count..7
2	Ace Goldfinger	4.99	NA	NA	2	3
3	Adaptation Holes	2.99	NA	NA	2	4
5	African Egg	2.99	NA	NA	2	3
8	Airport Pollock	4.99	NA	NA	2	4
13	Ali Forever	4.99	NA	NA	2	4
20	Amelie Hellfighters	4.99	1	3	NA	NA

10.9.8 Compute the outstanding balance.

```
rs <- dbGetQuery(
  con,
  "select sum(f.rental_rate) open_amt,count(*) count
                 from rental r
                      left outer join payment p
                        on r.rental_id = p.rental_id
                      join inventory i
                        on r.inventory_id = i.inventory_id
                      join film f
                        on i.film_id = f.film_id
                where p.rental_id is null
               ;"
)
sp_print_df(head(rs))
```

open_amt	count
4297.48	1452

10.10 Different strategies for interacting with the database

select examples dbGetQuery returns the entire result set as a data frame.
For large returned datasets, complex or inefficient SQL statements, this may take a long time.

```
  dbSendQuery: parses, compiles, creates the optimized execution plan.
      dbFetch: Execute optimzed execution plan and return the dataset.
dbClearResult: remove pending query results from the database to your R environment
```

10.10.1 Use dbGetQuery

How many customers are there in the DVD Rental System

```
rs1 <- dbGetQuery(con, "select * from customer;")
sp_print_df(head(rs1))
```

customer_id	store_id	first_name	last_name	email	address_id	activebool	crea
524	1	Jared	Ely	jared.ely@sakilacustomer.org	530	TRUE	200
1	1	Mary	Smith	mary.smith@sakilacustomer.org	5	TRUE	200
2	1	Patricia	Johnson	patricia.johnson@sakilacustomer.org	6	TRUE	200
3	1	Linda	Williams	linda.williams@sakilacustomer.org	7	TRUE	200
4	2	Barbara	Jones	barbara.jones@sakilacustomer.org	8	TRUE	200
5	1	Elizabeth	Brown	elizabeth.brown@sakilacustomer.org	9	TRUE	200

```
pco <- dbSendQuery(con, "select * from customer;")
rs2 <- dbFetch(pco)
dbClearResult(pco)
sp_print_df(head(rs2))
```

customer_id	store_id	first_name	last_name	email	address_id	activebool	crea
524	1	Jared	Ely	jared.ely@sakilacustomer.org	530	TRUE	200
1	1	Mary	Smith	mary.smith@sakilacustomer.org	5	TRUE	200
2	1	Patricia	Johnson	patricia.johnson@sakilacustomer.org	6	TRUE	200
3	1	Linda	Williams	linda.williams@sakilacustomer.org	7	TRUE	200
4	2	Barbara	Jones	barbara.jones@sakilacustomer.org	8	TRUE	200
5	1	Elizabeth	Brown	elizabeth.brown@sakilacustomer.org	9	TRUE	200

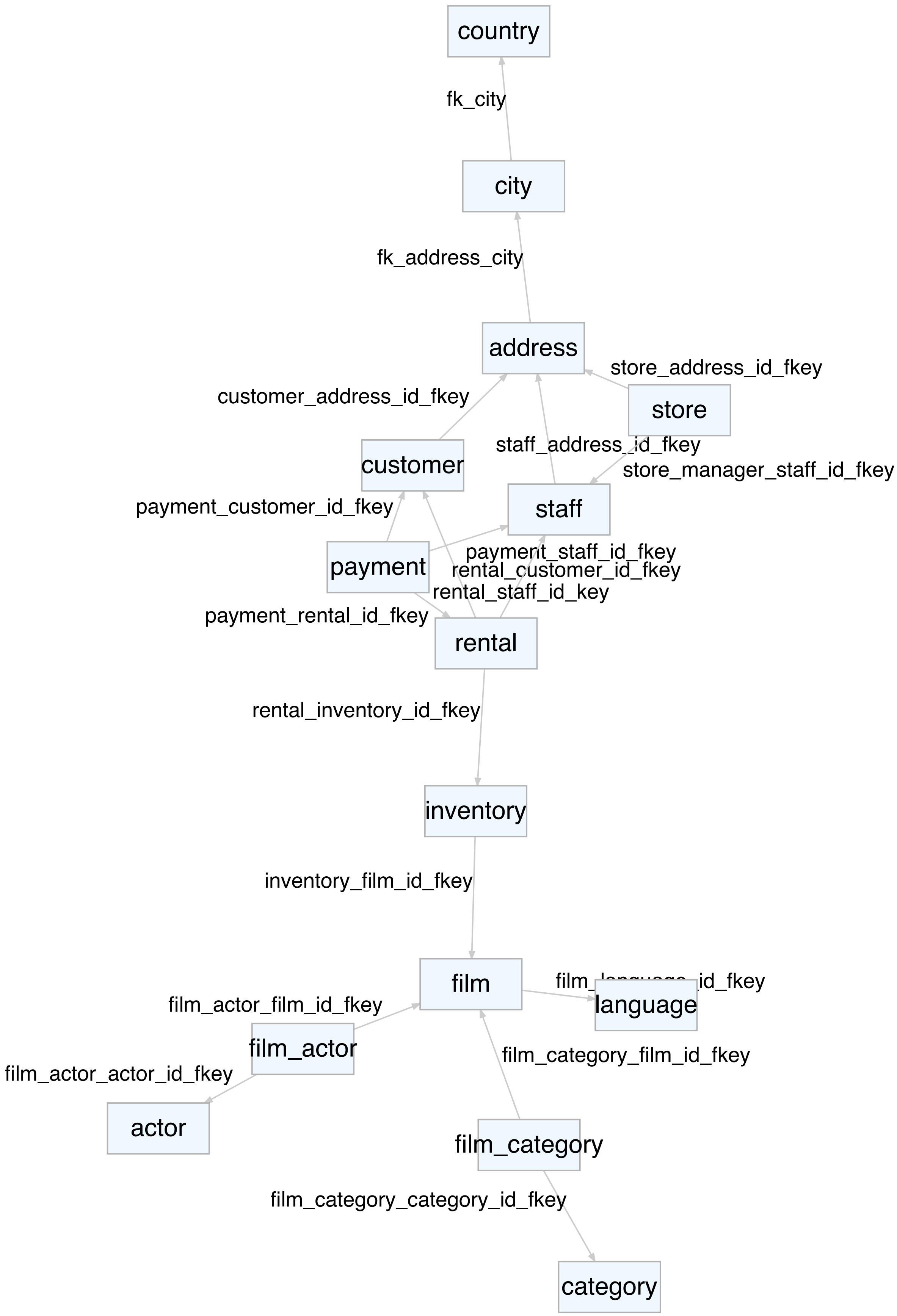
10.10.2 Use dbExecute

10.10.3 Anti join – Find Sophie who has never rented a movie.

```
customer_table <- DBI::dbReadTable(con, "customer")
rental_table <- DBI::dbReadTable(con, "rental")

customer_tbl <- dplyr::tbl(con, "customer")
rental_tbl <- dplyr::tbl(con, "rental")

dplyr_tbl_loj <-
  left_join(customer_tbl, rental_tbl, by = "customer_id", suffix = c(".c", ".r")) %>%
  filter(is.na(rental_id)) %>%
  select(c("first_name", "last_name", "email"))

rs <- dbGetQuery(
  con,
  "select c.first_name
                      ,c.last_name
                      ,c.email
                 from customer c
                      left outer join rental r
                           on c.customer_id = r.customer_id
                where r.rental_id is null;
              "
)
sp_print_df(head(rs))
```

first_name	last_name	email
Sophie	Yang	email@email.com

```
View(dplyr_tbl_loj)
```


country
fk_city
city
fk_address_city
address
store_address_id_fkey
customer_address_id_fkey
store
customer
staff_address_id_fkey
store_manager_staff_id_fkey
payment_customer_id_fkey
staff
payment
payment_staff_id_fkey
rental_customer_id_fkey
rental_staff_id_key
payment_rental_id_fkey
rental
rental_inventory_id_fkey
inventory
inventory_film_id_fkey
film
film_actor_film_id_fkey
language
film_actor
film_category_film_id_fkey
film_actor_actor_id_fkey
actor
film_category
film_category_category_id_fkey
category

```r
# diconnect from the db
dbDisconnect(con)

sp_docker_stop("sql-pet")
```

```
## [1] "sql-pet"
```

```r
knitr::knit_exit()
```

Chapter 11

SQL Quick start - simple retrieval (15)

Start up the `docker-pet` container

```
sp_docker_start("sql-pet")
```

Now connect to the `dvdrental` database with R

```
con <- sp_get_postgres_connection(
  user = Sys.getenv("DEFAULT_POSTGRES_USER_NAME"),
  password =  Sys.getenv("DEFAULT_POSTGRES_PASSWORD"),
  dbname = "dvdrental",
  seconds_to_test = 10)
con
```

```
## <PqConnection> dvdrental@localhost:5432
```

```
colFmt <- function(x,color)
{
  # x string
  # color
  outputFormat = knitr::opts_knit$get("rmarkdown.pandoc.to")
  if(outputFormat == 'latex')
    paste("\\textcolor{",color,"}{",x,"}",sep="")
  else if(outputFormat == 'html')
    paste("<font color='",color,"'>",x,"</font>",sep="")
  else
    x
}

# sample call
# * `r colFmt('Cover inline tables in future section','red')`
```

Moved this from 11-elementary-queries

```
dplyr_summary_df <-
    read.delim(
    '11-dplyr_sql_summary_table.tsv',
    header = TRUE,
    sep = '\t',
```

```
    as.is = TRUE
    )

head(dplyr_summary_df)
```

```
##   In          Dplyr_Function
## 1  Y               arrange()
## 2 Y?              distinct()
## 3  Y       select() rename()
## 4  N                  pull()
## 5  Y    mutate() transmute()
## 6  Y summarise() summarize()
##                                description
## 1                    Arrange rows by variables
## 2           Return rows with matching conditions
## 3                 Select/rename variables by name
## 4                      Pull out a single variable
## 5                               Add new variables
## 6 Reduces multiple values down to a single value
##                          SQL_Clause Notes                 Category
## 1                          ORDER BY    NA Basic single-table verbs
## 2                 SELECT distinct *    NA Basic single-table verbs
## 3       SELECT column_name alias_name    NA Basic single-table verbs
## 4               SELECT column_name;    NA Basic single-table verbs
## 5 SELECT computed_value computed_name    NA Basic single-table verbs
## 6 SELECT aggregate_functions GROUP BY    NA Basic single-table verbs
```

11.1 Databases and Third Normal Form - 3NF

Most relational database applications are designed to be third normal form "like", 3NF. The key benefits of 3NF are

1. speedy on-line transactional processing, OLTP.
2. improved referential integrity, reduce modification anomalies that can occur during an insert, update, or delete operation.
3. reduced storage, elimination of redundant data.

3NF is great for database application input performance, but not so great for getting the data back out for the data analyst or report writer. As a data analyst, you might get the ubiquitous Excel spreadsheet with all the information needed to start an Exploratory Data Analysis, EDA. The spreadsheet may have provider, patient, diagnosis, procedure, and insurance information all "neatly" arranged on a single row. At least "neatly" when compared to the same information stored in the database, in at least 5 tables.

For this tutorial, the most important thing to know about 3NF is that the data you are looking for gets spread across many many tables. Working in a relational database requires you to

1. find the many many different tables that contains your data.

2. Understand the relationships that tie the tables together correctly to ensure that data is not dropped or duplicated. Data that is dropped or duplicated can either over or understate your aggregated numeric values.

https://www.smartdraw.com/entity-relationship-diagram/examples/hospital-billing-entity-relationship-diagram/

Real life applications have 100's or even 1000's of tables supporting the application. The goal is to transform the application data model into a useful data analysis model using the DDL and DML SQL statements.

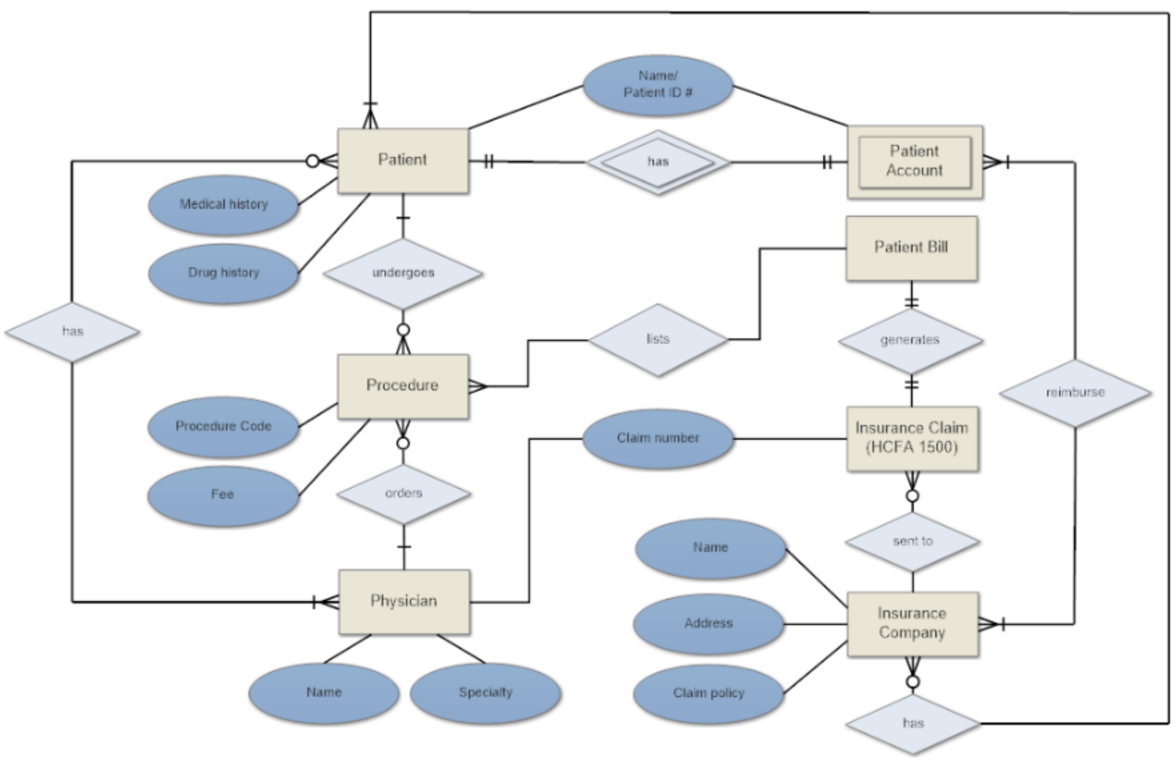


Figure 11.1: hospital-billing-erd

11.2 SQL Commands

SQL commands fall into four categories.

SQL Category	Definition
DDL:Data Definition Language	DBA's execute these commands to define objects in the database.
DML:Data Manipulation Language	Users and developers execute these commands to investigate data.
DCL:Data Control Language	DBA's execute these commands to grant/revoke access to
TCL:Transaction Control Language	Developers execute these commands when developing applications.

Data analysts use the SELECT DML command to learn interesting things about the data stored in the database. Applications are used to control the insert, update, and deletion of data in the database. Data users can update the database objects via the application which enforces referential integrity in the database. Data users should never directly update data application database objects. Leave this task to the developers and DBA's.

DBA's can setup a sandbox within the database for a data analyst. The application(s) do not maintain the data in the sandbox.

The `sql-pet` database is tiny, but for the purposes of these exercises, we assume that data so large that it will not easily fit into the memory of your laptop.

This tutorial focuses on the most frequently used SQL statement, the SQL SELECT statement.

A SQL SELECT statement consists of 1 to 6 clauses.

SQL Clause	DPLYR Verb	SQL Description
SELECT	SELECT() mutate()	Contains a list of column names from an object or a derived value.
FROM		Contains a list of related tables from which the SELECT list of columns is derived.
WHERE	filter()	Provides the filter conditions the objects in the FROM clause must meet.
GROUP BY	group_by()	Contains a list rollup aggregation columns.
HAVING		Provides the filter condition on the the GROUP BY clause.
ORDER BY	arrange()	Contains a list of column names indicating the order of the column value. Each column can be either ASCending or DEScending.

The foundation of the SQL language is based set theory and the result of a SQL SELECT statement is referred to as a result set. A SQL SELECT statement is "guaranteed" to return the same set of data, but not necessarily in the same order. However, in practice, the result set is usually in the same order.

SQL SELECT statements can be broken up into two categories, SELECT detail statements and SELECT aggregate statements.

Table 11.4: select all columns

store_id	manager_staff_id	address_id	last_update
1	1	1	2006-02-15 09:57:12
2	2	2	2006-02-15 09:57:12

SELECT DETAIL	SELECT AGGREGATE
select det_col1…det_coln	select det_agg1…, agg1,…,aggn
from same	from same
where same	where same
	group by det_agg1
	having
order by same	order by same

The difference between the two statements is the AGGREGATE has

1. select clause has one or more detail columns, det_agg1…, on which values get aggregated against/rolled up to.
2. select clause zero or more aggregated values, agg1, …, aggn
3. group by clause is required and matches the one or more detail columns, det_agg1.
4. having clause is optional and adds a filter condition on one or more agg1 … aggn values.

11.3 SQL SELECT Quick Start

This section focuses on getting new SQL users familiar with the six SQL query clauses and a single table. SQL queries from multiple tables are discussed in the JOIN section of this tutorial. The JOIN section resolves the issue introduced with 3NF, the splitting of data into many many tables, back into a denormalaized format similar to the Excel spreadsheet.

The DBI::dbGetQuery function is used to submit SQL SELECT statements to the Postgres database. At a minimum it requires two parameters, a connection object and a SQL SELECT statement.

In the following section we only look at SELECT DETAIL statements.

11.3.1 SELECT Clause: Column Selection – Vertical Partioning of Data

11.3.1.1 1. Simplest SQL query: All rows and all columns from a single table.

```
rs <-
  DBI::dbGetQuery(
  con,
  "
  select * from store;
  ")
kable(rs,caption = 'select all columns')
```

11.3.1.2 2. Same Query as 1, but only show first two columns;

Table 11.5: select first two columns only

store_id	manager_staff_id
1	1
2	2

Table 11.6: reverse the column order

manager_staff_id	store_id
1	1
2	2

```
rs <-
  DBI::dbGetQuery(
  con,
  "
  select STORE_ID, manager_staff_id from store;
  ")
kable(rs,caption = 'select first two columns only')
```

11.3.1.3 3. Same Query as 2, but reverse the column order

dvdrental=# select manager_staff_id,store_id from store;

```
rs <-
  DBI::dbGetQuery(
  con,
  "
  select manager_staff_id,store_id from store;
  ")
kable(rs,caption = 'reverse the column order')
```

11.3.1.4 4. Rename Columns – SQL column alias in the result set

```
rs <-
  DBI::dbGetQuery(
  con,
  "
  select manager_staff_id mgr_sid,store_id st_id from store;
  ")
kable(rs,caption = 'Rename Columns')
```

`The manager_staff_id has changed to mgr_sid.`

Table 11.7: Rename Columns

mgr_sid	st_id
1	1
2	2

Table 11.8: Adding Meta Data Columns

showing	store_id	manager_staff_id	address_id	last_update	db	user	dtts
derived column	1	1	1	2006-02-15 09:57:12	dvdrental	postgres	2018/11/02 0
derived column	2	2	2	2006-02-15 09:57:12	dvdrental	postgres	2018/11/02 0

```
store_id has changed to st_id.

Note that the column names have changed in the result set only, not in the actual database table.
The DBA's will not allow a space or other special characters in a database table column name.

Some motivations for aliasing the result set column names are

  1.  Some database table column names are not user friendly.
 2.  When multiple tables are joined, the column names may be the same in one or more tables and one needs to d
```

11.3.1.5 5. Adding Meta Data Columns to the Result Set

```
rs <-
  DBI::dbGetQuery(
  con,
  "
  select 'derived column' showing
        ,*
        ,current_database() db
        ,user
        ,to_char(now(),'YYYY/MM/DD HH24:MI:SS') dtts
    from store;
  ")
kable(rs,caption = 'Adding Meta Data Columns')
```

```
All the previous examples easily fit on a single line.  This one is longer.  Each column is entered on its own

1.  The showing column is a hard coded string surrounded by single quotes.  Note that single quotes are for har
2.  The db and dtts, date timestamp, are new columns generated from Postgres System Information Functions.
3.  Note that `user` is not a function call, no parenthesis.
```

11.3.2 SQL Comments

SQL supports both a single line comment, preceed the line with two dashes, `--`, and a C like block comment, * … */.

11.3.2.1 6. Single line comment –

```
rs <-
  DBI::dbGetQuery(
  con,
  "
  select 'single line comment, dtts' showing
```

Table 11.9: Sincle line comment

showing	store_id	manager_staff_id	address_id	last_update	db	user
single line comment, dtts	1	1	1	2006-02-15 09:57:12	dvdrental	postgres
single line comment, dtts	2	2	2	2006-02-15 09:57:12	dvdrental	postgres

Table 11.10: Multi-line comment

showing	store_id	manager_staff_id	address_id	last_update
block comment drop db, user, and dtts	1	1	1	2006-02-15 09:57:12
block comment drop db, user, and dtts	2	2	2	2006-02-15 09:57:12

```
        ,*
        ,current_database() db
        ,user
    --  ,to_char(now(),'YYYY/MM/DD HH24:MI:SS') dtts
    from store;
  ")
kable(rs,caption = 'Sincle line comment')
```

`The dtts  line is commented out with the two dashes and is dropped from the end of the result set columns.`

11.3.2.2 7. Multi-line comment /*…*/

```
rs <-
  DBI::dbGetQuery(
  con,
  "
  select 'block comment drop db, user, and dtts' showing
        ,*
        /*
        ,current_database() db
        ,user
        ,to_char(now(),'YYYY/MM/DD HH24:MI:SS') dtts
        */
    from store;
  ")
kable(rs,caption = 'Multi-line comment')
```

`The three columns db, user, and dtts, between the /\* and \*/ have been commented and no longer appear as the c`

11.3.3 FROM Clause

The `FROM` clause contains one or more datasets, usually database tables/views, from which the `SELECT` columns are derived. For now, in the examples, we are only using a single table. If the database reflects a relational model, your data is likely spread out over several tables. The key take away when beginning your analysis is to pick the table that has most of the data that you need for your analysis. This table becomes your main or driving table to build your SQL query statement around. After identifying your driving table, potentially save yourself a lot of time and heart ache, review any view that is built on your driving table. If one or more exist, especially, if vendor built, may already have the additional information needed for your analysis.

Insert SQL here or link to Views dependent on what

In this tutorial, there is only a single user hitting the database and row/table locking is not necessary and considered out of scope.

11.3.3.1 Table Uses

- A table can be used more than once in a FROM clause. These are self-referencing tables. An example is an EMPLOYEE table which contains a foriegn key to her manager. Her manager also has a foriegn key to her manager, etc up the corporate ladder.

- In the example above, the EMPLOYEE table plays two roles, employee and manager. The next line shows the FROM clause showing the same table used twice.

  FROM EMPLOYEE EE, EMPLOYEE MGR
- The EE and MGR are aliases for the EMPLOYEE table and represent the different roles the EMPLOYEE table plays.

- Since all the column names are exactly the same for the EE and MGR role, the column names need to be prefixed with their role alias, e.g., SELECT MGR.EE_NAME, EE.EE_NAME ... shows the manager name and her employee name(s) who work for her.
- It is a good habit to always alias your tables and prefix your column names with the table alias to eliminate any ambiguity as to where the column came from. This is critical where there is inconsistent table column naming convention. It also helps when debugging larger SQL queries.
- Cover inline tables in future section

`Side Note: Do not create an unintended Cartesian join. If one has more than one table in the FROM clause, mak`

11.3.4 WHERE Clause: Row Selection – Horizontal Partitioning of Data

In the previous SELECT clause section, the SELECT statement either partitioned data vertically across the table columns or derived vertical column values. This section provides examples that partitions the table data across rows in the table.

The WHERE clause defines all the conditions the data must meet to be included or excluded in the final result set. If all the conditions are met data is returned or it is rejected. This is commonly referred to as the data set filter condition.

`Side Note: For performance optimization reasons, the WHERE clause should reduce the dataset down to the small`

The WHERE condition(s) can be simple or complex, but in the end are the appliction of the logic rules shown in the table below.

p	q	p and q	p or q
T	T	T	T
T	F	F	T
T	N	N	T
F	F	F	F
F	N	F	T
N	N	N	N

When the filter logic is complex, it is sometimes easier to represent the where clause symbollically and apply a version of DeMorgan's law which is shown below.

Table 11.12: select all columns

store_id	manager_staff_id	address_id	last_update
1	1	1	2006-02-15 09:57:12
2	2	2	2006-02-15 09:57:12

Table 11.13: WHERE always FALSE

store_id	manager_staff_id	address_id	last_update

1. (A and B)' = A' or B'
2. (A or B)' = A' and B'

11.3.4.1 Examples Continued

We begin with 1, our simplest SQL query.

```
rs <-
  DBI::dbGetQuery(
  con,
  "
  select * from store;
  ")
kable(rs,caption = 'select all columns')
```

11.3.4.2 8 WHERE condition logically never TRUE.

```
rs <-
  DBI::dbGetQuery(
  con,
  "
  select * from store where 1 = 0;
  ")
kable(rs,caption = 'WHERE always FALSE')
```

```
Since 1 = 0 is always false, no rows are ever returned.  Initially this construct seems useless, but actually
```

11.3.4.3 9 WHERE condition logically always TRUE.

```
rs <-
  DBI::dbGetQuery(
  con,
  "
  select * from store where 1 = 1;
  ")
kable(rs,caption = 'WHERE always TRUE')
```

```
Since 1 = 1 is always true, all rows are always returned.  Initially this construct seems useless, but actuall
```

Table 11.14: WHERE always TRUE

store_id	manager_staff_id	address_id	last_update
1	1	1	2006-02-15 09:57:12
2	2	2	2006-02-15 09:57:12

Table 11.15: WHERE EQUAL

store_id	manager_staff_id	address_id	last_update
2	2	2	2006-02-15 09:57:12

11.3.4.4 10 WHERE equality condition

```
rs <-
  DBI::dbGetQuery(
  con,
  "
  select * from store where store_id = 2;
  ")
kable(rs,caption = 'WHERE EQUAL')
```

```
The only row where the store_id = 2 is row 2 and it is the only row returned.
```

11.3.4.5 11 WHERE NOT equal conditions

```
rs <-
  DBI::dbGetQuery(
  con,
  "
  select * from store where store_id <> 2;
  ")
kable(rs,caption = 'WHERE NOT EQUAL')
```

```
<> is syntactically the same as !=

    The only row where the store_id <> 2 is row 1 and only row 1 is returned.
```

11.3.4.6 12 WHERE OR condition

```
rs <-
  DBI::dbGetQuery(
  con,
  "
```

Table 11.16: WHERE NOT EQUAL

store_id	manager_staff_id	address_id	last_update
1	1	1	2006-02-15 09:57:12

Table 11.17: WHERE OR condition

store_id	manager_staff_id	address_id	last_update
1	1	1	2006-02-15 09:57:12
2	2	2	2006-02-15 09:57:12

```
  select * from store where manager_staff_id = 1 or store_id < 3;
  ")
kable(rs,caption = 'WHERE OR condition')
```

`The first condition manager_staff_id = 1 returns a single row and the second condition store_id < 3 returns tw`

Following table is modified from http://www.tutorialspoint.com/sql/sql-operators

SQL Comparison Operators

Operator	Description	example
=	Checks if the values of two operands are equal or not, if yes then condition becomes true.	(a = b) is not true.
!=	Checks if the values of two operands are equal or not, if values are not equal then condition becomes true.	(a != b) is true.
<>	Checks if the values of two operands are equal or not, if values are not equal then condition becomes true.	(a <> b) is true.
>	Checks if the value of left operand is greater than the value of right operand, if yes then condition becomes true.	(a > b) is not true.
<	Checks if the value of left operand is less than the value of right operand, if yes then condition becomes true.	(a < b) is true.
>=	Checks if the value of left operand is greater than or equal to the value of right operand, if yes then condition becomes true.	(a >= b) is not true.
<=	Checks if the value of left operand is less than or equal to the value of right operand, if yes then condition becomes true.	(a <= b) is true.
!<	Checks if the value of left operand is not less than the value of right operand, if yes then condition becomes true.	(a !< b) is false.
!>	Checks if the value of left operand is not greater than the value of right operand, if yes then condition becomes true.	(a !> b) is true.

Operator	Description
ALL	The ALL operator is used to compare a value to all values in another value set.
AND	The AND operator allows the existence of multiple conditions in an SQL statement's WHERE clause.
ANY	The ANY operator is used to compare a value to any applicable value in the list as per the condition.
BETWEEN	The BETWEEN operator is used to search for values that are within a set of values, given the minimum value and the maximum value.
EXISTS	The EXISTS operator is used to search for the presence of a row in a specified table that meets a certain criterion.
IN	The IN operator is used to compare a value to a list of literal values that have been specified.
LIKE	The LIKE operator is used to compare a value to similar values using wildcard operators.
NOT	The NOT operator reverses the meaning of the logical operator with which it is used. Eg: NOT EXISTS, NOT BETWEEN, NOT IN, etc. This is a negate operator.
OR	The OR operator is used to combine multiple conditions in an SQL statement's WHERE clause.
IS NULL	The NULL operator is used to compare a value with a NULL value.
UNIQUE	The UNIQUE operator searches every row of a specified table for uniqueness (no duplicates).

https://pgexercises.com/questions/basic

TO-DO's

1. inline tables
2. correlated subqueries

11.4 Paradigm Shift from R-Dplyr to SQL

Paraphrasing what some have said with an R dplyr background and no SQL experience, "It is like working from the inside out." This sentiment occurs because

1. The SQL SELECT statement begins at the end, the SELECT clause, and drills backwards, loosely speaking, to derive the desired result set.
2. SQL SELECT statements are an all or nothing proposition. One gets nothing if there is any kind of syntax error.

3. SQL SELECT result sets can be quite opaque. The WHERE clause can be very dense and difficult to trace through. It is rarely ever linear in nature.

4. Validating all the permutations in the where clause can be tough and tedious.

11.4.1 Big bang versus piped incremental steps.

1. Dplyr starts with one or more sources joined together in a conceptually similar way that SQL joins sources.
2. The pipe and filter() function breaks down the filter conditions into small managable logical steps. This makes it much easier to understand what is happening in the derivation of the final tibble. Adding tees through out the pipe line gives one full trace back of all the data transformations at every pipe.

Helpful tidyverse functions that output tibbles: tbl_module function in https://github.com/nhemerson/tibbleColumns package;

Mental picture: SQL approach: Imagine a data lake named Niagera Falls and drinking from it without drowning. R-Dplyr approach: Imagine a resturant at the bottom of the Niagera Falls data lake and having a refreshing dring out of the water faucet.

11.4.2 SQL Execution Order

The table below is derived from this site. https://www.periscopedata.com/blog/sql-query-order-of-operations It shows what goes on under the hood SQL SELECT hood.

SEQ	SQL	Function	Dplyr
1	WITH	Common Table expression, CTE, one or more datasets/tables used FROM clause.	.data parameter in dplyr functions
2	FROM	Choose and join tables to get base data	.data parameter in dplyr functions
3	ON	Choose and join tables to get base data	dplyr join family of functions
4	JOIN	Choose and join tables to get base data	dplyr join family of functions
5	WHERE	filters the base data	dplyr filter()
6	GROUP BY	aggregates the base data	dplyr group_by family of functions

SEQ	SQL	Function	Dplyr
7	WITH CUBE/ROLLUP	aggregates the base data	is this part of the dplyr grammar
8	HAVING	filters aggregated data	dplyr filter()
9	SELECT	Returns final data set	dplyr select()
10	DISTINCT	Dedupe the final data set	dplyr distinct()
11	ORDER BY	Sorts the final data set	arrange()
12	TOP/LIMIT	Limits the number of rows in data set	
13	OFFSET/FETCH	Limits the number of rows in data set	

The SEQ column shows the standard order of SQL execution. One take away for this tutorial is that the SELECT clause actually executes late in the process, even though it is the first clause in the entire SELECT statement. A second take away is that SQL execution order, or tweaked order, plays a critical role in SQL query tuning.

6. SQL for View table dependencies.
7. Add cartesian join exercise.

Chapter 12

Getting metadata about and from the database (21)

The following packages are used in this chapter:

```
library(tidyverse)
library(DBI)
library(RPostgres)
library(glue)
library(here)
require(knitr)
library(dbplyr)
library(sqlpetr)
```

Assume that the Docker container with PostgreSQL and the dvdrental database are ready to go.

```
sp_docker_start("sql-pet")
```

Connect to the database:

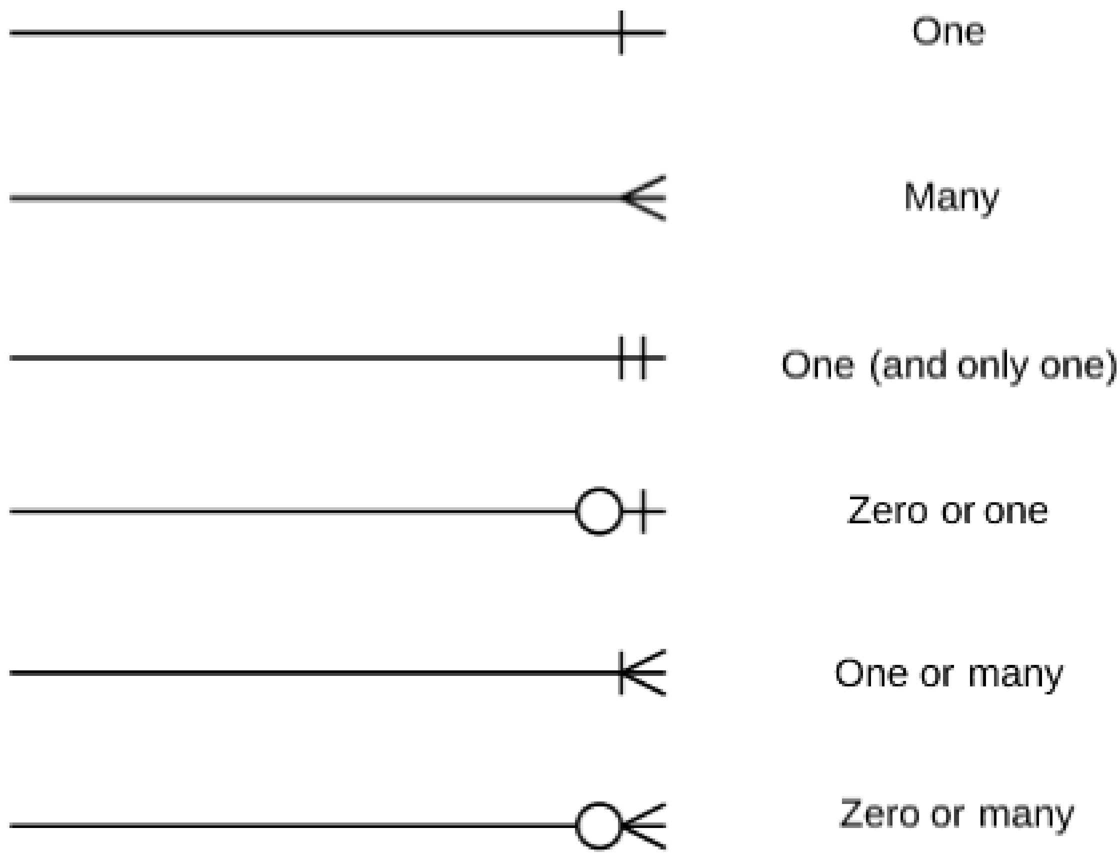
```
con <- sp_get_postgres_connection(
  user = Sys.getenv("DEFAULT_POSTGRES_USER_NAME"),
  password = Sys.getenv("DEFAULT_POSTGRES_PASSWORD"),
  dbname = "dvdrental",
  seconds_to_test = 10
)
```

12.1 Database contents and structure

After just looking at the data you seek, it might be worthwhile stepping back and looking at the big picture.

12.1.1 Database structure

For large or complex databases you need to use both the available documentation for your database (e.g., the dvdrental database) and the other empirical tools that are available. For example it's worth learning to interpret the symbols in an Entity Relationship Diagram:



The `information_schema` is a trove of information *about* the database. Its format is more or less consistent across the different SQL implementations that are available. Here we explore some of what's available using several different methods. Postgres stores a lot of metadata.

12.1.2 Contents of the `information_schema`

For this chapter R needs the `dbplyr` package to access alternate schemas. A schema is an object that contains one or more tables. Most often there will be a default schema, but to access the metadata, you need to explicitly specify which schema contains the data you want.

12.1.3 What tables are in the database?

The simplest way to get a list of tables is with

```
table_list <- DBI::dbListTables(con)

kable(table_list)
```

x
actor_info
customer_list
film_list
nicer_but_slower_film_list
sales_by_film_category
staff
sales_by_store
staff_list
category
film_category
country
actor
language
inventory
payment
rental
city
store
film
address
film_actor
customer
smy_film

12.1.4 Digging into the `information_schema`

We usually need more detail than just a list of tables. Most SQL databases have an `information_schema` that has a standard structure to describe and control the database.

The `information_schema` is in a different schema from the default, so to connect to the `tables` table in the `information_schema` we connect to the database in a different way:

```
table_info_schema_table <- tbl(con, dbplyr::in_schema("information_schema", "tables"))
```

The `information_schema` is large and complex and contains 211 tables. So it's easy to get lost in it.

This query retrieves a list of the tables in the database that includes additional detail, not just the name of the table.

```
table_info <- table_info_schema_table %>%
  filter(table_schema == "public") %>%
  select(table_catalog, table_schema, table_name, table_type) %>%
  arrange(table_type, table_name) %>%
  collect()

kable(table_info)
```

table_catalog	table_schema	table_name	table_type
dvdrental	public	actor	BASE TABLE
dvdrental	public	address	BASE TABLE
dvdrental	public	category	BASE TABLE
dvdrental	public	city	BASE TABLE
dvdrental	public	country	BASE TABLE
dvdrental	public	customer	BASE TABLE
dvdrental	public	film	BASE TABLE
dvdrental	public	film_actor	BASE TABLE
dvdrental	public	film_category	BASE TABLE
dvdrental	public	inventory	BASE TABLE
dvdrental	public	language	BASE TABLE
dvdrental	public	payment	BASE TABLE
dvdrental	public	rental	BASE TABLE
dvdrental	public	smy_film	BASE TABLE
dvdrental	public	staff	BASE TABLE
dvdrental	public	store	BASE TABLE
dvdrental	public	actor_info	VIEW
dvdrental	public	customer_list	VIEW
dvdrental	public	film_list	VIEW
dvdrental	public	nicer_but_slower_film_list	VIEW
dvdrental	public	sales_by_film_category	VIEW
dvdrental	public	sales_by_store	VIEW
dvdrental	public	staff_list	VIEW

In this context `table_catalog` is synonymous with `database`.

Notice that *VIEWS* are composites made up of one or more *BASE TABLES*.

The SQL world has its own terminology. For example `rs` is shorthand for `result set`. That's equivalent to using `df` for a `data frame`. The following SQL query returns the same information as the previous one.

```
rs <- dbGetQuery(
  con,
  "select table_catalog, table_schema, table_name, table_type
  from information_schema.tables
  where table_schema not in ('pg_catalog','information_schema')
  order by table_type, table_name
  ;"
)
kable(rs)
```

table_catalog	table_schema	table_name	table_type
dvdrental	public	actor	BASE TABLE
dvdrental	public	address	BASE TABLE
dvdrental	public	category	BASE TABLE
dvdrental	public	city	BASE TABLE
dvdrental	public	country	BASE TABLE
dvdrental	public	customer	BASE TABLE
dvdrental	public	film	BASE TABLE
dvdrental	public	film_actor	BASE TABLE
dvdrental	public	film_category	BASE TABLE
dvdrental	public	inventory	BASE TABLE
dvdrental	public	language	BASE TABLE
dvdrental	public	payment	BASE TABLE
dvdrental	public	rental	BASE TABLE
dvdrental	public	smy_film	BASE TABLE
dvdrental	public	staff	BASE TABLE
dvdrental	public	store	BASE TABLE
dvdrental	public	actor_info	VIEW
dvdrental	public	customer_list	VIEW
dvdrental	public	film_list	VIEW
dvdrental	public	nicer_but_slower_film_list	VIEW
dvdrental	public	sales_by_film_category	VIEW
dvdrental	public	sales_by_store	VIEW
dvdrental	public	staff_list	VIEW

12.2 What columns do those tables contain?

Of course, the `DBI` package has a `dbListFields` function that provides the simplest way to get the minimum, a list of column names:

```
DBI::dbListFields(con, "rental")
```

```
## [1] "rental_id"    "rental_date"  "inventory_id" "customer_id"
## [5] "return_date"  "staff_id"     "last_update"
```

But the `information_schema` has a lot more useful information that we can use.

```
columns_info_schema_table <- tbl(con, dbplyr::in_schema("information_schema", "columns"))
```

Since the `information_schema` contains 1868 columns, we are narrowing our focus to just one table. This query retrieves more information about the `rental` table:

```
columns_info_schema_info <- columns_info_schema_table %>%
  filter(table_schema == "public") %>%
  select(
    table_catalog, table_schema, table_name, column_name, data_type, ordinal_position,
    character_maximum_length, column_default, numeric_precision, numeric_precision_radix
  ) %>%
  collect(n = Inf) %>%
  mutate(data_type = case_when(
    data_type == "character varying" ~ paste0(data_type, " (", character_maximum_length, ")"),
    data_type == "real" ~ paste0(data_type, " (", numeric_precision, ",", numeric_precision_radix, ")")
    TRUE ~ data_type
  )) %>%
  filter(table_name == "rental") %>%
```

```
  select(-table_schema, -numeric_precision, -numeric_precision_radix)

glimpse(columns_info_schema_info)
```

```
## Observations: 7
## Variables: 7
## $ table_catalog            <chr> "dvdrental", "dvdrental", "dvdrental"...
## $ table_name               <chr> "rental", "rental", "rental", "rental...
## $ column_name              <chr> "rental_id", "rental_date", "inventor...
## $ data_type                <chr> "integer", "timestamp without time zo...
## $ ordinal_position         <int> 1, 2, 3, 4, 5, 6, 7
## $ character_maximum_length <int> NA, NA, NA, NA, NA, NA, NA
## $ column_default           <chr> "nextval('rental_rental_id_seq'::regc...
```

```
kable(columns_info_schema_info)
```

table_catalog	table_name	column_name	data_type	ordinal_position	character_maximum_
dvdrental	rental	rental_id	integer	1	
dvdrental	rental	rental_date	timestamp without time zone	2	
dvdrental	rental	inventory_id	integer	3	
dvdrental	rental	customer_id	smallint	4	
dvdrental	rental	return_date	timestamp without time zone	5	
dvdrental	rental	staff_id	smallint	6	
dvdrental	rental	last_update	timestamp without time zone	7	

12.2.1 What is the difference between a `VIEW` and a `BASE TABLE`?

The `BASE TABLE` has the underlying data in the database

```
table_info_schema_table %>%
  filter(table_schema == "public" & table_type == "BASE TABLE") %>%
  select(table_name, table_type) %>%
  left_join(columns_info_schema_table, by = c("table_name" = "table_name")) %>%
  select(
    table_type, table_name, column_name, data_type, ordinal_position,
    column_default
  ) %>%
  collect(n = Inf) %>%
  filter(str_detect(table_name, "cust")) %>%
  kable()
```

table_type	table_name	column_name	data_type	ordinal_position	column_default
BASE TABLE	customer	store_id	smallint	2	NA
BASE TABLE	customer	first_name	character varying	3	NA
BASE TABLE	customer	last_name	character varying	4	NA
BASE TABLE	customer	email	character varying	5	NA
BASE TABLE	customer	address_id	smallint	6	NA
BASE TABLE	customer	active	integer	10	NA
BASE TABLE	customer	customer_id	integer	1	nextval('customer_cu
BASE TABLE	customer	activebool	boolean	7	true
BASE TABLE	customer	create_date	date	8	('now'::text)::date
BASE TABLE	customer	last_update	timestamp without time zone	9	now()

Probably should explore how the `VIEW` is made up of data from BASE TABLEs.

```
table_info_schema_table %>%
  filter(table_schema == "public" & table_type == "VIEW") %>%
  select(table_name, table_type) %>%
  left_join(columns_info_schema_table, by = c("table_name" = "table_name")) %>%
  select(
    table_type, table_name, column_name, data_type, ordinal_position,
    column_default
  ) %>%
  collect(n = Inf) %>%
  filter(str_detect(table_name, "cust")) %>%
  kable()
```

table_type	table_name	column_name	data_type	ordinal_position	column_default
VIEW	customer_list	id	integer	1	NA
VIEW	customer_list	name	text	2	NA
VIEW	customer_list	address	character varying	3	NA
VIEW	customer_list	zip code	character varying	4	NA
VIEW	customer_list	phone	character varying	5	NA
VIEW	customer_list	city	character varying	6	NA
VIEW	customer_list	country	character varying	7	NA
VIEW	customer_list	notes	text	8	NA
VIEW	customer_list	sid	smallint	9	NA

12.2.2 What data types are found in the database?

```
columns_info_schema_info %>% count(data_type)
```

```
## # A tibble: 3 x 2
##   data_type                       n
##   <chr>                       <int>
## 1 integer                         2
## 2 smallint                        2
## 3 timestamp without time zone     3
```

12.3 Characterizing how things are named

Names are the handle for accessing the data. Tables and columns may or may not be named consistently or in a way that makes sense to you. You should look at these names *as data*.

12.3.1 Counting columns and name reuse

Pull out some rough-and-ready but useful statistics about your database. Since we are in SQL-land we talk about variables as `columns`.

```
public_tables <- columns_info_schema_table %>%
  filter(table_schema == "public") %>%
  collect()

public_tables %>%
  count(table_name, sort = TRUE) %>% head(n = 15) %>%
  kable()
```

table_name	n
film	13
smy_film	13
staff	11
customer	10
customer_list	9
address	8
film_list	8
nicer_but_slower_film_list	8
staff_list	8
rental	7
payment	6
actor	4
actor_info	4
city	4
inventory	4

How many *column names* are shared across tables (or duplicated)?

```
public_tables %>% count(column_name, sort = TRUE) %>% filter(n > 1)
```

```
## # A tibble: 40 x 2
##    column_name     n
##    <chr>       <int>
##  1 last_update    15
##  2 film_id         5
##  3 address_id      4
##  4 description     4
##  5 first_name      4
##  6 last_name       4
##  7 length          4
##  8 name            4
##  9 rating          4
## 10 store_id        4
## # ... with 30 more rows
```

How many column names are unique?

```
public_tables %>% count(column_name) %>% filter(n == 1) %>% count()
```

```
## # A tibble: 1 x 1
##      nn
##   <int>
## 1    18
```

12.4 Database keys

12.4.1 Direct SQL

How do we use this output? Could it be generated by dplyr?

```
rs <- dbGetQuery(
  con,
  "
--SELECT conrelid::regclass as table_from
```

```
select table_catalog||'.'||table_schema||'.'||table_name table_name
, conname, pg_catalog.pg_get_constraintdef(r.oid, true) as condef
FROM information_schema.columns c,pg_catalog.pg_constraint r
WHERE 1 = 1 --r.conrelid = '16485'
  AND r.contype  in ('f','p') ORDER BY 1
;"
)
glimpse(rs)
```

```
## Observations: 61,644
## Variables: 3
## $ table_name <chr> "dvdrental.information_schema.administrable_role_au...
## $ conname    <chr> "actor_pkey", "actor_pkey", "actor_pkey", "country_...
## $ condef     <chr> "PRIMARY KEY (actor_id)", "PRIMARY KEY (actor_id)",...
```

```
kable(head(rs))
```

table_name	conname	condef
dvdrental.information_schema.administrable_role_authorizations	actor_pkey	PRIMARY KEY (actor_id)
dvdrental.information_schema.administrable_role_authorizations	actor_pkey	PRIMARY KEY (actor_id)
dvdrental.information_schema.administrable_role_authorizations	actor_pkey	PRIMARY KEY (actor_id)
dvdrental.information_schema.administrable_role_authorizations	country_pkey	PRIMARY KEY (country_id)
dvdrental.information_schema.administrable_role_authorizations	country_pkey	PRIMARY KEY (country_id)
dvdrental.information_schema.administrable_role_authorizations	country_pkey	PRIMARY KEY (country_id)

The following is more compact and looks more useful. What is the difference between the two?

```
rs <- dbGetQuery(
  con,
  "select conrelid::regclass as table_from
      ,c.conname
      ,pg_get_constraintdef(c.oid)
  from pg_constraint c
  join pg_namespace n on n.oid = c.connamespace
 where c.contype in ('f','p')
   and n.nspname = 'public'
order by conrelid::regclass::text, contype DESC;
"
)
glimpse(rs)
```

```
## Observations: 33
## Variables: 3
## $ table_from           <chr> "actor", "address", "address", "category"...
## $ conname              <chr> "actor_pkey", "address_pkey", "fk_address...
## $ pg_get_constraintdef <chr> "PRIMARY KEY (actor_id)", "PRIMARY KEY (a...
```

```
kable(head(rs))
```

table_from	conname	pg_get_constraintdef
actor	actor_pkey	PRIMARY KEY (actor_id)
address	address_pkey	PRIMARY KEY (address_id)
address	fk_address_city	FOREIGN KEY (city_id) REFERENCES city(city_id)
category	category_pkey	PRIMARY KEY (category_id)
city	city_pkey	PRIMARY KEY (city_id)
city	fk_city	FOREIGN KEY (country_id) REFERENCES country(country_id)

```
dim(rs)[1]
```

```
## [1] 33
```

12.4.2 Database keys with dplyr

This query shows the primary and foreign keys in the database.

```
tables <- tbl(con, dbplyr::in_schema("information_schema", "tables"))
table_constraints <- tbl(con, dbplyr::in_schema("information_schema", "table_constraints"))
key_column_usage <- tbl(con, dbplyr::in_schema("information_schema", "key_column_usage"))
referential_constraints <- tbl(con, dbplyr::in_schema("information_schema", "referential_constraints"))
constraint_column_usage <- tbl(con, dbplyr::in_schema("information_schema", "constraint_column_usage"))

keys <- tables %>%
  left_join(table_constraints, by = c(
    "table_catalog" = "table_catalog",
    "table_schema" = "table_schema",
    "table_name" = "table_name"
  )) %>%
  # table_constraints %>%
  filter(constraint_type %in% c("FOREIGN KEY", "PRIMARY KEY")) %>%
  left_join(key_column_usage,
    by = c(
      "table_catalog" = "table_catalog",
      "constraint_catalog" = "constraint_catalog",
      "constraint_schema" = "constraint_schema",
      "table_name" = "table_name",
      "table_schema" = "table_schema",
      "constraint_name" = "constraint_name"
    )
  ) %>%
  # left_join(constraint_column_usage) %>% # does this table add anything useful?
  select(table_name, table_type, constraint_name, constraint_type, column_name, ordinal_position) %>%
  arrange(table_name) %>%
  collect()
glimpse(keys)
```

```
## Observations: 35
## Variables: 6
## $ table_name       <chr> "actor", "address", "address", "category", "c...
## $ table_type       <chr> "BASE TABLE", "BASE TABLE", "BASE TABLE", "BA...
## $ constraint_name  <chr> "actor_pkey", "address_pkey", "fk_address_cit...
## $ constraint_type  <chr> "PRIMARY KEY", "PRIMARY KEY", "FOREIGN KEY", ...
## $ column_name      <chr> "actor_id", "address_id", "city_id", "categor...
## $ ordinal_position <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, ...
```

```
kable(keys)
```

table_name	table_type	constraint_name	constraint_type	column_name	ordinal_pos
actor	BASE TABLE	actor_pkey	PRIMARY KEY	actor_id	
address	BASE TABLE	address_pkey	PRIMARY KEY	address_id	
address	BASE TABLE	fk_address_city	FOREIGN KEY	city_id	
category	BASE TABLE	category_pkey	PRIMARY KEY	category_id	
city	BASE TABLE	city_pkey	PRIMARY KEY	city_id	
city	BASE TABLE	fk_city	FOREIGN KEY	country_id	
country	BASE TABLE	country_pkey	PRIMARY KEY	country_id	
customer	BASE TABLE	customer_address_id_fkey	FOREIGN KEY	address_id	
customer	BASE TABLE	customer_pkey	PRIMARY KEY	customer_id	
film	BASE TABLE	film_language_id_fkey	FOREIGN KEY	language_id	
film	BASE TABLE	film_pkey	PRIMARY KEY	film_id	
film_actor	BASE TABLE	film_actor_actor_id_fkey	FOREIGN KEY	actor_id	
film_actor	BASE TABLE	film_actor_film_id_fkey	FOREIGN KEY	film_id	
film_actor	BASE TABLE	film_actor_pkey	PRIMARY KEY	actor_id	
film_actor	BASE TABLE	film_actor_pkey	PRIMARY KEY	film_id	
film_category	BASE TABLE	film_category_category_id_fkey	FOREIGN KEY	category_id	
film_category	BASE TABLE	film_category_film_id_fkey	FOREIGN KEY	film_id	
film_category	BASE TABLE	film_category_pkey	PRIMARY KEY	film_id	
film_category	BASE TABLE	film_category_pkey	PRIMARY KEY	category_id	
inventory	BASE TABLE	inventory_film_id_fkey	FOREIGN KEY	film_id	
inventory	BASE TABLE	inventory_pkey	PRIMARY KEY	inventory_id	
language	BASE TABLE	language_pkey	PRIMARY KEY	language_id	
payment	BASE TABLE	payment_customer_id_fkey	FOREIGN KEY	customer_id	
payment	BASE TABLE	payment_pkey	PRIMARY KEY	payment_id	
payment	BASE TABLE	payment_rental_id_fkey	FOREIGN KEY	rental_id	
payment	BASE TABLE	payment_staff_id_fkey	FOREIGN KEY	staff_id	
rental	BASE TABLE	rental_customer_id_fkey	FOREIGN KEY	customer_id	
rental	BASE TABLE	rental_inventory_id_fkey	FOREIGN KEY	inventory_id	
rental	BASE TABLE	rental_pkey	PRIMARY KEY	rental_id	
rental	BASE TABLE	rental_staff_id_key	FOREIGN KEY	staff_id	
staff	BASE TABLE	staff_address_id_fkey	FOREIGN KEY	address_id	
staff	BASE TABLE	staff_pkey	PRIMARY KEY	staff_id	
store	BASE TABLE	store_address_id_fkey	FOREIGN KEY	address_id	
store	BASE TABLE	store_manager_staff_id_fkey	FOREIGN KEY	manager_staff_id	
store	BASE TABLE	store_pkey	PRIMARY KEY	store_id	

What do we learn from the following query? How is it useful?

```
rs <- dbGetQuery(
  con,
  "SELECT r.*,
  pg_catalog.pg_get_constraintdef(r.oid, true) as condef
  FROM pg_catalog.pg_constraint r
  WHERE 1=1 --r.conrelid = '16485' AND r.contype = 'f' ORDER BY 1;
  "
)

head(rs)
```

```
##                          conname connamespace contype condeferrable
## 1 cardinal_number_domain_check        12703       c         FALSE
## 2               yes_or_no_check        12703       c         FALSE
## 3                    year_check         2200       c         FALSE
```

```
## 4                   actor_pkey         2200       p         FALSE
## 5                 address_pkey         2200       p         FALSE
## 6                category_pkey         2200       p         FALSE
##   condeferred convalidated conrelid contypid conindid confrelid
## 1       FALSE         TRUE        0    12716        0         0
## 2       FALSE         TRUE        0    12724        0         0
## 3       FALSE         TRUE        0    16397        0         0
## 4       FALSE         TRUE    16420        0    16555         0
## 5       FALSE         TRUE    16461        0    16557         0
## 6       FALSE         TRUE    16427        0    16559         0
##   confupdtype confdeltype confmatchtype conislocal coninhcount
## 1                                             TRUE           0
## 2                                             TRUE           0
## 3                                             TRUE           0
## 4                                             TRUE           0
## 5                                             TRUE           0
## 6                                             TRUE           0
##   connoinherit conkey confkey conpfeqop conppeqop conffeqop conexclop
## 1        FALSE   <NA>    <NA>      <NA>      <NA>      <NA>      <NA>
## 2        FALSE   <NA>    <NA>      <NA>      <NA>      <NA>      <NA>
## 3        FALSE   <NA>    <NA>      <NA>      <NA>      <NA>      <NA>
## 4         TRUE    {1}    <NA>      <NA>      <NA>      <NA>      <NA>
## 5         TRUE    {1}    <NA>      <NA>      <NA>      <NA>      <NA>
## 6         TRUE    {1}    <NA>      <NA>      <NA>      <NA>      <NA>
##
## 1
## 2 {SCALARARRAYOPEXPR :opno 98 :opfuncid 67 :useOr true :inputcollid 100 :args ({RELABELTYPE :arg {COERCET
## 3                                                                          {BOOLEXPR :boolop and :args
## 4
## 5
## 6
##                                                                                                consrc
## 1                                                                                        (VALUE >= 0)
## 2 ((VALUE)::text = ANY ((ARRAY['YES'::character varying, 'NO'::character varying])::text[]))
## 3                                                          ((VALUE >= 1901) AND (VALUE <= 2155))
## 4                                                                                                <NA>
## 5                                                                                                <NA>
## 6                                                                                                <NA>
##                                                                                                condef
## 1                                                                                  CHECK (VALUE >= 0)
## 2 CHECK (VALUE::text = ANY (ARRAY['YES'::character varying, 'NO'::character varying]::text[]))
## 3                                                          CHECK (VALUE >= 1901 AND VALUE <= 2155)
## 4                                                                            PRIMARY KEY (actor_id)
## 5                                                                          PRIMARY KEY (address_id)
## 6                                                                         PRIMARY KEY (category_id)
```

12.5 Creating your own data dictionary

If you are going to work with a database for an extended period it can be useful to create your own data dictionary. This can take the form of keeping detaild notes as well as extracting metadata from the dbms. Here is an illustration of the idea.

```r
some_tables <- c("rental", "city", "store")

all_meta <- map_df(some_tables, sp_get_dbms_data_dictionary, con = con)

all_meta
```

```
## # A tibble: 15 x 11
##    table_name var_name var_type num_rows num_blank num_unique min   q_25
##    <chr>      <chr>    <chr>       <int>     <int>      <int> <chr> <chr>
##  1 rental     rental_~ integer     16044         0      16044 1     4013
##  2 rental     rental_~ double      16044         0      15815 2005~ 2005~
##  3 rental     invento~ integer     16044         0       4580 1     1154
##  4 rental     custome~ integer     16044         0        599 1     148
##  5 rental     return_~ double      16044       183      15836 2005~ 2005~
##  6 rental     staff_id integer     16044         0          2 1     1
##  7 rental     last_up~ double      16044         0          3 2006~ 2006~
##  8 city       city_id  integer       600         0        600 1     150
##  9 city       city     charact~      600         0        599 A Co~ Dzer~
## 10 city       country~ integer       600         0        109 1     28
## 11 city       last_up~ double        600         0          1 2006~ 2006~
## 12 store      store_id integer         2         0          2 1     1
## 13 store      manager~ integer         2         0          2 1     1
## 14 store      address~ integer         2         0          2 1     1
## 15 store      last_up~ double          2         0          1 2006~ 2006~
## # ... with 3 more variables: q_50 <chr>, q_75 <chr>, max <chr>
```

```r
glimpse(all_meta)
```

```
## Observations: 15
## Variables: 11
## $ table_name <chr> "rental", "rental", "rental", "rental", "rental", "...
## $ var_name   <chr> "rental_id", "rental_date", "inventory_id", "custom...
## $ var_type   <chr> "integer", "double", "integer", "integer", "double"...
## $ num_rows   <int> 16044, 16044, 16044, 16044, 16044, 16044, 16044, 60...
## $ num_blank  <int> 0, 0, 0, 0, 183, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0
## $ num_unique <int> 16044, 15815, 4580, 599, 15836, 2, 3, 600, 599, 109...
## $ min        <chr> "1", "2005-05-24 22:53:30", "1", "1", "2005-05-25 2...
## $ q_25       <chr> "4013", "2005-07-07 00:58:00", "1154", "148", "2005...
## $ q_50       <chr> "8025", "2005-07-28 16:03:27", "2291", "296", "2005...
## $ q_75       <chr> "12037", "2005-08-17 21:13:35", "3433", "446", "200...
## $ max        <chr> "16049", "2006-02-14 15:16:03", "4581", "599", "200...
```

```r
kable(head(all_meta))
```

table_name	var_name	var_type	num_rows	num_blank	num_unique	min	q_25
rental	rental_id	integer	16044	0	16044	1	4013
rental	rental_date	double	16044	0	15815	2005-05-24 22:53:30	2005-07-07 00:
rental	inventory_id	integer	16044	0	4580	1	1154
rental	customer_id	integer	16044	0	599	1	148
rental	return_date	double	16044	183	15836	2005-05-25 23:55:21	2005-07-10 15:
rental	staff_id	integer	16044	0	2	1	1

12.6 Save your work!

The work you do to understand the structure and contents of a database can be useful for others (including future-you). So at the end of a session, you might look at all the data frames you want to save. Consider saving them in a form where you can add notes at the appropriate level (as in a Google Doc representing table or columns that you annotate over time).

```
ls()
```

```
##  [1] "all_meta"                  "columns_info_schema_info"
##  [3] "columns_info_schema_table" "con"
##  [5] "constraint_column_usage"   "cranex"
##  [7] "key_column_usage"          "keys"
##  [9] "public_tables"             "referential_constraints"
## [11] "rs"                        "some_tables"
## [13] "table_constraints"         "table_info"
## [15] "table_info_schema_table"   "table_list"
## [17] "tables"
```

Chapter 13

Drilling into your DBMS environment (22)

The following packages are used in this chapter:

```
# These packages are called in almost every chapter of the book:
library(tidyverse)
library(DBI)
library(RPostgres)
require(knitr)
library(dbplyr)
library(sqlpetr)

display_rows <-  15 # as a default, show 15 rows
```

Start up the `docker-pet` container

```
sp_docker_start("sql-pet")
```

Now connect to the `dvdrental` database with R

```
con <- sp_get_postgres_connection(
  user = Sys.getenv("DEFAULT_POSTGRES_USER_NAME"),
  password = Sys.getenv("DEFAULT_POSTGRES_PASSWORD"),
  dbname = "dvdrental",
  seconds_to_test = 10
)
con
```

```
## <PqConnection> dvdrental@localhost:5432
```

13.1 Which database?

Your DBA will create your user accounts and priviledges for the database(s) that you can access.

One of the challenges when working with a database(s) is finding where your data actually resides. Your best resources will be one or more subject matter experts, `SME`, and your DBA. Your data may actually reside in multiple databases, e.g., a detail and summary databases. In our tutorial, we focus on the one database, `dvdrental`. Database names usually reflect something about the data that they contain.

Your laptop is a server for the Docker Postgres databases. A database is a collection of files that Postgres manages in the background.

13.2 How many databases reside in the Docker Container?

```
rs <-
  DBI::dbGetQuery(
    con,
    "SELECT 'DB Names in Docker' showing
          ,datname DB
     FROM pg_database
    WHERE datistemplate = false;
  "
  )
kable(rs)
```

showing	db
DB Names in Docker	postgres
DB Names in Docker	dvdrental

Which databases are available?

```
Modify the connection call to connect to the `postgres` database.
```

```
con <- sp_get_postgres_connection(
  user = Sys.getenv("DEFAULT_POSTGRES_USER_NAME"),
  password = Sys.getenv("DEFAULT_POSTGRES_PASSWORD"),
  dbname = "your code goes here",
  seconds_to_test = 10
)

con
```

```
## [1] "There is no connection"
```

```
if (con != "There is no connection") {
  dbDisconnect(con)
}

# Answer: con <PqConnection> postgres@localhost:5432

# Reconnect to dvdrental

con <- sp_get_postgres_connection(
  user = Sys.getenv("DEFAULT_POSTGRES_USER_NAME"),
  password = Sys.getenv("DEFAULT_POSTGRES_PASSWORD"),
  dbname = "dvdrental",
  seconds_to_test = 10
)
con
```

```
## <PqConnection> dvdrental@localhost:5432
```

Note that the two Sys.getenv function calls work in this tutorial because both the user and password are available in both databases. This is a common practice in organinzations that have implemented single sign on across their organization.

```
Gotcha:

If one has data in multiple databases or multiple environments, Development,
Integration, and Prodution, it is very easy to connect to the wrong database in
the wrong environment.  Always double check your connection information when
logging in and before performing any inserts, updates, or deletes against the
database.
```

The following code block should be used to reduce propagating the above gotcha. Current_database(), CURRENT_DATE or CURRENT_TIMESTAMP, and 'result set' are the most useful and last three not so much. Instead of the host IP address having the actual hostname would be a nice addition.

```
rs1 <-
  DBI::dbGetQuery(
    con,
    "SELECT current_database() DB
         ,CURRENT_DATE
         ,CURRENT_TIMESTAMP
         ,'result set description' showing
         ,session_user
         ,inet_server_addr() host
         ,inet_server_port() port
  "
  )
kable(rs1)
```

db	current_date	current_timestamp	showing	session_user	host	port
dvdrental	2018-11-02	2018-11-01 17:08:19	result set description	postgres	172.17.0.2	5432

Since we will only be working in the `dvdrental` database in this tutorial and reduce the number of output columns shown, only the 'result set description' will be used.

13.3 Which Schema?

In the code block below, we look at the `information_schema.table` which contains information about all the schemas and table/views within our dvdrental database. Databases can have one or more schemas, containers that hold tables or views. Schemas partition the database into big logical blocks of related data. Schema names usually reflect an application or logically related datasets. Occasionally a DBA will set up a new schema and use a users name.

What schemas are in the `dvdrental` database? How many entries are in each schema?

```
## Database Schemas
#
rs1 <-
  DBI::dbGetQuery(
    con,
    "SELECT 'DB Schemas' showing,t.table_catalog DB,t.table_schema,COUNT(*) tbl_vws
     FROM information_schema.tables t
    GROUP BY t.table_catalog,t.table_schema
  "
  )
kable(rs1)
```

showing	db	table_schema	tbl_vws
DB Schemas	dvdrental	pg_catalog	121
DB Schemas	dvdrental	public	23
DB Schemas	dvdrental	information_schema	67

We see that there are three schemas. The pg_catalog is the standard PostgreSQL meta data and core schema. Postgres uses this schema to manage the internal workings of the database. DBA's are the primary users of pg_catalog. We used the pg_catalog schema to answer the question 'How many databases reside in the Docker Container?', but normally the data analyst is not interested in analyzing database data.

The information_schema contains ANSI standardized views used across the different SQL vendors, (Oracle, Sysbase, MS SQL Server, IBM DB2, etc). The information_schema contains a plethora of metadata that will help you locate your data tables, understand the relationships between the tables, and write efficient SQL queries.

13.4 Exercises

```
#
# Add an order by clause to order the output by the table catalog.
rs1 <- DBI::dbGetQuery(con, "SELECT '1. ORDER BY table_catalog' showing
                              ,t.table_catalog DB,t.table_schema,COUNT(*) tbl_vws
                          FROM information_schema.tables t
                        GROUP BY t.table_catalog,t.table_schema
                        ")
kable(rs1)
```

showing	db	table_schema	tbl_vws
1. ORDER BY table_catalog	dvdrental	pg_catalog	121
1. ORDER BY table_catalog	dvdrental	public	23
1. ORDER BY table_catalog	dvdrental	information_schema	67

```
# Add an order by clause to order the output by tbl_vws in descending order.
rs2 <- DBI::dbGetQuery(con, "SELECT '2. ORDER BY tbl_vws desc' showing
                              ,t.table_catalog DB,t.table_schema,COUNT(*) tbl_vws
                          FROM information_schema.tables t
                        GROUP BY t.table_catalog,t.table_schema
                        ")
kable(rs2)
```

showing	db	table_schema	tbl_vws
2. ORDER BY tbl_vws desc	dvdrental	pg_catalog	121
2. ORDER BY tbl_vws desc	dvdrental	public	23
2. ORDER BY tbl_vws desc	dvdrental	information_schema	67

```
# Complete the SQL statement to show everything about all the tables.

rs3 <- DBI::dbGetQuery(con, "SELECT '3. all information_schema tables' showing
                              ,'your code goes here'
                          FROM information_schema.tables t
                        ")
kable(head(rs3, display_rows))
```

showing	?column?
3. all information_schema tables	your code goes here
3. all information_schema tables	your code goes here
3. all information_schema tables	your code goes here
3. all information_schema tables	your code goes here
3. all information_schema tables	your code goes here
3. all information_schema tables	your code goes here
3. all information_schema tables	your code goes here
3. all information_schema tables	your code goes here
3. all information_schema tables	your code goes here
3. all information_schema tables	your code goes here
3. all information_schema tables	your code goes here
3. all information_schema tables	your code goes here
3. all information_schema tables	your code goes here
3. all information_schema tables	your code goes here
3. all information_schema tables	your code goes here

```
# Use the results from above to pull interesting columns from just the information_schema
rs4 <- DBI::dbGetQuery(con, "SELECT '4. information_schema.tables' showing
                                     ,'your code goes here'
                                 FROM information_schema.tables t
                                where 'your code goes here' = 'your code goes here'
                              ")
head(rs4, display_rows)
```

```
##                         showing           ?column?
## 1  4. information_schema.tables your code goes here
## 2  4. information_schema.tables your code goes here
## 3  4. information_schema.tables your code goes here
## 4  4. information_schema.tables your code goes here
## 5  4. information_schema.tables your code goes here
## 6  4. information_schema.tables your code goes here
## 7  4. information_schema.tables your code goes here
## 8  4. information_schema.tables your code goes here
## 9  4. information_schema.tables your code goes here
## 10 4. information_schema.tables your code goes here
## 11 4. information_schema.tables your code goes here
## 12 4. information_schema.tables your code goes here
## 13 4. information_schema.tables your code goes here
## 14 4. information_schema.tables your code goes here
## 15 4. information_schema.tables your code goes here
```

```
# Modify the SQL below with your interesting column names.
# Update the where clause to return only rows from the information schema and begin with 'tab'
rs5 <- DBI::dbGetQuery(con, "SELECT '5. information_schema.tables' showing
                                     ,'your code goes here'
                                 FROM information_schema.tables t
                                where 'your code goes here' = 'your code goes here'
                              ")
kable(head(rs5, display_rows))
```

showing	?column?
5. information_schema.tables	your code goes here
5. information_schema.tables	your code goes here
5. information_schema.tables	your code goes here
5. information_schema.tables	your code goes here
5. information_schema.tables	your code goes here
5. information_schema.tables	your code goes here
5. information_schema.tables	your code goes here
5. information_schema.tables	your code goes here
5. information_schema.tables	your code goes here
5. information_schema.tables	your code goes here
5. information_schema.tables	your code goes here
5. information_schema.tables	your code goes here
5. information_schema.tables	your code goes here
5. information_schema.tables	your code goes here
5. information_schema.tables	your code goes here

```
# Modify the SQL below with your interesting column names.
# Update the where clause to return only rows from the information schema and begin with 'col'
rs6 <- DBI::dbGetQuery(con, "SELECT '6. information_schema.tables' showing
                                    ,'your code goes here'
                               FROM information_schema.tables t
                              where 'your code goes here' = 'your code goes here'
                            ")
kable(head(rs6, display_rows))
```

showing	?column?
6. information_schema.tables	your code goes here
6. information_schema.tables	your code goes here
6. information_schema.tables	your code goes here
6. information_schema.tables	your code goes here
6. information_schema.tables	your code goes here
6. information_schema.tables	your code goes here
6. information_schema.tables	your code goes here
6. information_schema.tables	your code goes here
6. information_schema.tables	your code goes here
6. information_schema.tables	your code goes here
6. information_schema.tables	your code goes here
6. information_schema.tables	your code goes here
6. information_schema.tables	your code goes here
6. information_schema.tables	your code goes here
6. information_schema.tables	your code goes here

In the next exercise we combine both the table and column output from the previous exercises. Review the following code block. The last two lines of the WHERE clause are swithced. Will the result set be the same or different? Execute the code block and review the two datasets.

```
rs7 <- DBI::dbGetQuery(con, "SELECT '7. information_schema.tables' showing
                                    ,table_catalog||'.'||table_schema db_info, table_name, table_type
                               FROM information_schema.tables t
                              where table_schema = 'information_schema'
                                and table_name like 'table%' OR table_name like '%col%'
                                and table_type = 'VIEW'
                            ")
kable(head(rs7, display_rows))
```

showing	db_info	table_name	table_type
7. information_schema.tables	dvdrental.information_schema	collations	VIEW
7. information_schema.tables	dvdrental.information_schema	collation_character_set_applicability	VIEW
7. information_schema.tables	dvdrental.information_schema	column_domain_usage	VIEW
7. information_schema.tables	dvdrental.information_schema	column_privileges	VIEW
7. information_schema.tables	dvdrental.information_schema	column_udt_usage	VIEW
7. information_schema.tables	dvdrental.information_schema	columns	VIEW
7. information_schema.tables	dvdrental.information_schema	constraint_column_usage	VIEW
7. information_schema.tables	dvdrental.information_schema	key_column_usage	VIEW
7. information_schema.tables	dvdrental.information_schema	role_column_grants	VIEW
7. information_schema.tables	dvdrental.information_schema	table_constraints	VIEW
7. information_schema.tables	dvdrental.information_schema	table_privileges	VIEW
7. information_schema.tables	dvdrental.information_schema	tables	VIEW
7. information_schema.tables	dvdrental.information_schema	triggered_update_columns	VIEW
7. information_schema.tables	dvdrental.information_schema	view_column_usage	VIEW
7. information_schema.tables	dvdrental.information_schema	_pg_foreign_table_columns	VIEW

```
rs8 <- DBI::dbGetQuery(con, "SELECT '8. information_schema.tables' showing
                              ,table_catalog||'.'||table_schema db_info, table_name, table_type
                            FROM information_schema.tables t
                           where table_schema = 'information_schema'
                             and table_type = 'VIEW'
                             and table_name like 'table%' OR table_name like '%col%'
                         ")
kable(head(rs8, display_rows))
```

showing	db_info	table_name	table_type
8. information_schema.tables	dvdrental.information_schema	column_options	VIEW
8. information_schema.tables	dvdrental.information_schema	_pg_foreign_table_columns	VIEW
8. information_schema.tables	dvdrental.information_schema	view_column_usage	VIEW
8. information_schema.tables	dvdrental.information_schema	triggered_update_columns	VIEW
8. information_schema.tables	dvdrental.information_schema	tables	VIEW
8. information_schema.tables	dvdrental.information_schema	table_privileges	VIEW
8. information_schema.tables	dvdrental.information_schema	table_constraints	VIEW
8. information_schema.tables	dvdrental.information_schema	role_column_grants	VIEW
8. information_schema.tables	dvdrental.information_schema	key_column_usage	VIEW
8. information_schema.tables	dvdrental.information_schema	constraint_column_usage	VIEW
8. information_schema.tables	dvdrental.information_schema	columns	VIEW
8. information_schema.tables	dvdrental.information_schema	column_udt_usage	VIEW
8. information_schema.tables	dvdrental.information_schema	column_privileges	VIEW
8. information_schema.tables	dvdrental.information_schema	column_domain_usage	VIEW
8. information_schema.tables	dvdrental.information_schema	collation_character_set_applicability	VIEW

Operator/Element	Associativity	Description
.	left	table/column name separator
::	left	PostgreSQL-style typecast
[ ]	left	array element selection
-	right	unary minus
^	left	exponentiation
/ %	left	multiplication, division, modulo
+ -	left	addition, subtraction
IS		IS TRUE, IS FALSE, IS UNKNOWN, IS NULL
ISNULL		test for null
NOTNULL		test for not null

Operator/Element	Associativity	Description
(any other)	left	all other native and user-defined operators
IN		set membership
BETWEEN		range containment
OVERLAPS		time interval overlap
LIKE ILIKE SIMILAR		string pattern matching
< >		less than, greater than
=	right	equality, assignment
NOT	right	logical negation
AND	left	logical conjunction
OR	left	logical disjunction

```
rs1 <- DBI::dbGetQuery(con, "SELECT t.table_catalog DB ,t.table_schema
                                  ,t.table_name,t.table_type
                              FROM information_schema.tables t")

rs2 <- DBI::dbGetQuery(con, "SELECT t.table_catalog DB ,t.table_schema
                                  ,t.table_type,COUNT(*) tbls
                              FROM information_schema.tables t
                            group by t.table_catalog ,t.table_schema
                                  ,t.table_type
                            ")

rs3 <- DBI::dbGetQuery(con, "SELECT distinct t.table_catalog DB ,t.table_schema
                                  ,t.table_type tbls
                              FROM information_schema.tables t
                            ")



# kable(head(rs1 %>% arrange (table_name)))
# View(rs1)
# View(rs2)
# View(rs3)
kable(head(rs1))
```

db	table_schema	table_name	table_type
dvdrental	public	actor_info	VIEW
dvdrental	public	customer_list	VIEW
dvdrental	public	film_list	VIEW
dvdrental	public	nicer_but_slower_film_list	VIEW
dvdrental	public	sales_by_film_category	VIEW
dvdrental	public	staff	BASE TABLE

```
kable(head(rs2))
```

db	table_schema	table_type	tbls
dvdrental	information_schema	BASE TABLE	7
dvdrental	information_schema	VIEW	60
dvdrental	pg_catalog	BASE TABLE	62
dvdrental	public	BASE TABLE	16
dvdrental	public	VIEW	7
dvdrental	pg_catalog	VIEW	59

```r
kable(head(rs3))
```

db	table_schema	tbls
dvdrental	information_schema	BASE TABLE
dvdrental	information_schema	VIEW
dvdrental	pg_catalog	BASE TABLE
dvdrental	public	BASE TABLE
dvdrental	public	VIEW
dvdrental	pg_catalog	VIEW

www.dataquest.io/blog/postgres-internals

Comment on the practice of putting a comma at the beginning of a line in SQL code.

```r
## Explain a `dplyr::join

tbl_pk_fk_df <- DBI::dbGetQuery(
  con,
  "
SELECT --t.table_catalog,t.table_schema,
   c.table_name
    ,kcu.column_name
    ,c.constraint_name
    ,c.constraint_type
    ,coalesce(c2.table_name, '') ref_table
    ,coalesce(kcu2.column_name, '') ref_table_col
FROM information_schema.tables t
LEFT JOIN information_schema.table_constraints c
  ON t.table_catalog = c.table_catalog
    AND t.table_schema = c.table_schema
    AND t.table_name = c.table_name
LEFT JOIN information_schema.key_column_usage kcu
    ON c.constraint_schema = kcu.constraint_schema
        AND c.constraint_name = kcu.constraint_name
LEFT JOIN information_schema.referential_constraints rc
    ON c.constraint_schema = rc.constraint_schema
        AND c.constraint_name = rc.constraint_name
LEFT JOIN information_schema.table_constraints c2
    ON rc.unique_constraint_schema = c2.constraint_schema
        AND rc.unique_constraint_name = c2.constraint_name
LEFT JOIN information_schema.key_column_usage kcu2
    ON c2.constraint_schema = kcu2.constraint_schema
        AND c2.constraint_name = kcu2.constraint_name
        AND kcu.ordinal_position = kcu2.ordinal_position
WHERE c.constraint_type IN ('PRIMARY KEY', 'FOREIGN KEY')
  AND c.table_catalog = 'dvdrental'
    AND c.table_schema = 'public'
ORDER BY c.table_name;
"
)

# View(tbl_pk_fk_df)

tables_df <- tbl_pk_fk_df %>% distinct(table_name)
# View(tables_df)
```

```r
library(DiagrammeR)

table_nodes_ndf <- create_node_df(
  n <- nrow(tables_df)
  , type <- "table"
  , label <- tables_df$table_name
  ,
  shape = "rectangle"
  , width = 1
  , height = .5
  , fontsize = 18
)

tbl_pk_fk_ids_df <- inner_join(tbl_pk_fk_df, table_nodes_ndf
  ,
  by = c("table_name" = "label")
  , suffix(c("st", "s"))
) %>%
  rename("src_tbl_id" = id) %>%
  left_join(table_nodes_ndf
    ,
    by = c("ref_table" = "label")
    , suffix(c("st", "t"))
  ) %>%
  rename("fk_tbl_id" = id)

tbl_fk_df <- tbl_pk_fk_ids_df %>% filter(constraint_type == "FOREIGN KEY")
tbl_pk_df <- tbl_pk_fk_ids_df %>% filter(constraint_type == "PRIMARY KEY")
# View(tbl_pk_fk_ids_df)
# View(tbl_fk_df)
# View(tbl_pk_df)
kable(head(tbl_fk_df))
```

table_name	column_name	constraint_name	constraint_type	ref_table	ref_table_col	src_tbl_id
address	city_id	fk_address_city	FOREIGN KEY	city	city_id	2
city	country_id	fk_city	FOREIGN KEY	country	country_id	4
customer	address_id	customer_address_id_fkey	FOREIGN KEY	address	address_id	6
film	language_id	film_language_id_fkey	FOREIGN KEY	language	language_id	7
film_actor	actor_id	film_actor_actor_id_fkey	FOREIGN KEY	actor	actor_id	8
film_actor	film_id	film_actor_film_id_fkey	FOREIGN KEY	film	film_id	8

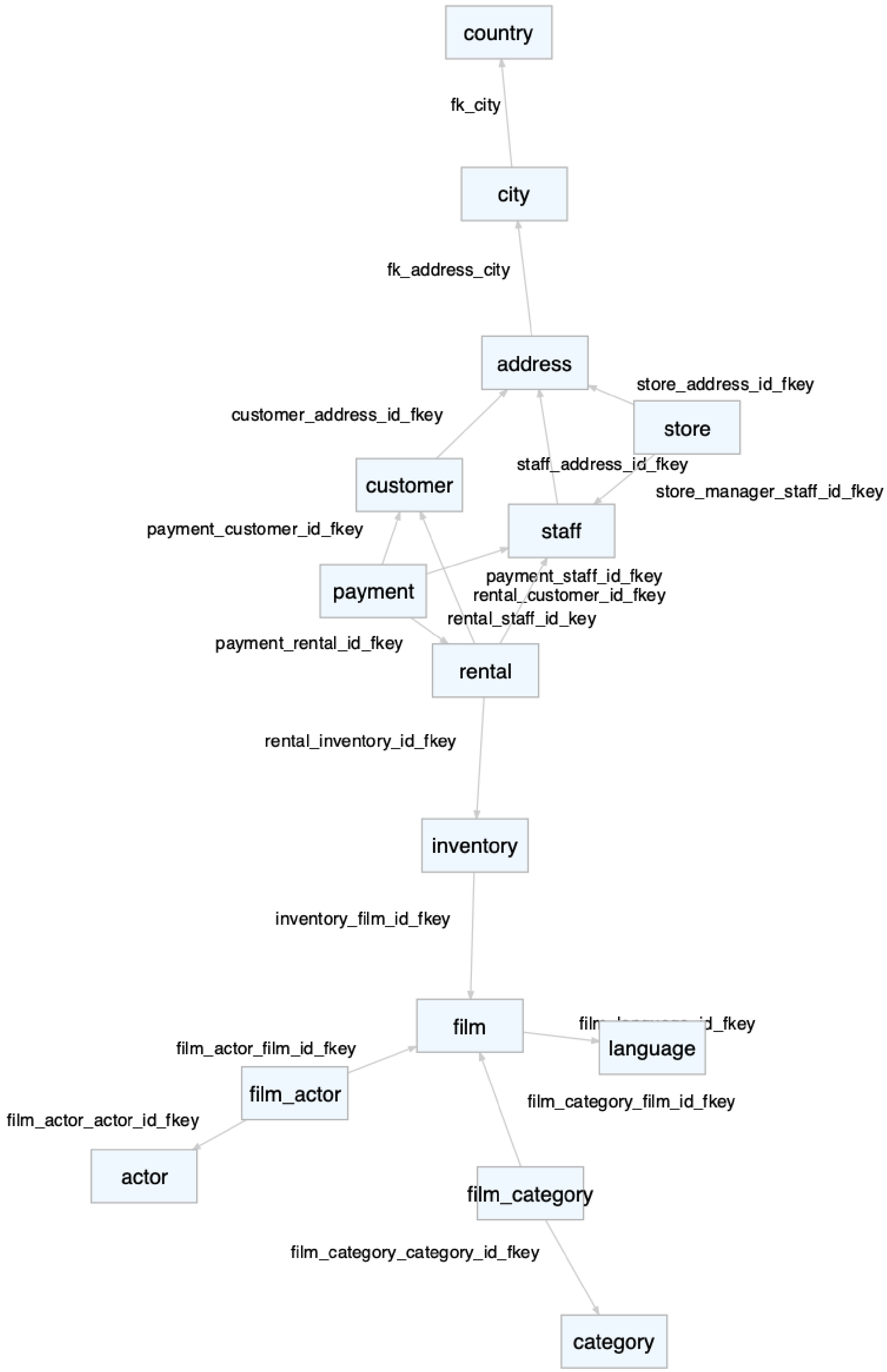
```r
kable(head(tbl_pk_df))
```

table_name	column_name	constraint_name	constraint_type	ref_table	ref_table_col	src_tbl_id	type.x
actor	actor_id	actor_pkey	PRIMARY KEY			1	table
address	address_id	address_pkey	PRIMARY KEY			2	table
category	category_id	category_pkey	PRIMARY KEY			3	table
city	city_id	city_pkey	PRIMARY KEY			4	table
country	country_id	country_pkey	PRIMARY KEY			5	table
customer	customer_id	customer_pkey	PRIMARY KEY			6	table

```r
# Create an edge data frame, edf

fk_edf <-
  create_edge_df(
```

```
    from = tbl_fk_df$src_tbl_id,
    to = tbl_fk_df$fk_tbl_id,
    rel = "fk",
    label = tbl_fk_df$constraint_name,
    fontsize = 15
  )
# View(fk_edf)
```

```
fkgraph_widget <-
  create_graph(
    nodes_df = table_nodes_ndf,
    edges_df = fk_edf,
    graph_name = "Simple FK Graph"
  ) %>%
  render_graph()

# export to image files
fkgraph_file <- sqlpetr::sp_make_image_files(
  fkgraph_widget,
  "diagrams",
  "fkgraph"
)
```


country
fk_city
city
fk_address_city
address
store_address_id_fkey
customer_address_id_fkey
store
customer
staff_address_id_fkey
store_manager_staff_id_fkey
payment_customer_id_fkey
staff
payment
payment_staff_id_fkey
rental_customer_id_fkey
rental_staff_id_key
payment_rental_id_fkey
rental
rental_inventory_id_fkey
inventory
inventory_film_id_fkey
film
film_actor_film_id_fkey
language
film_actor
film_category_film_id_fkey
film_actor_actor_id_fkey
actor
film_category
film_category_category_id_fkey
category

```
dbDisconnect(con)
# system2('docker','stop sql-pet')
```

Chapter 14

Explain queries (71)

- examining `dplyr` queries (`dplyr::show_query` on the R side v EXPLAIN on the PostgreSQL side)

Start up the `docker-pet` container

```
sp_docker_start("sql-pet")
```

now connect to the database with R

```
con <- sp_get_postgres_connection(user = Sys.getenv("DEFAULT_POSTGRES_USER_NAME"),
                         password = Sys.getenv("DEFAULT_POSTGRES_PASSWORD"),
                         dbname = "dvdrental",
                         seconds_to_test = 10)
```

14.1 Performance considerations

```
## Explain a `dplyr::join`

## Explain the quivalent SQL join
rs1 <- DBI::dbGetQuery(con
                 ,"SELECT c.*
                     FROM pg_catalog.pg_class c
                     JOIN pg_catalog.pg_namespace n ON n.oid = c.relnamespace
                    WHERE  n.nspname = 'public'
                      AND  c.relname = 'cust_movies'
                      AND  c.relkind = 'r'
                   ;
                 "
                 )
head(rs1)
```

```
##  [1] relname             relnamespace        reltype
##  [4] reloftype           relowner            relam
##  [7] relfilenode         reltablespace       relpages
## [10] reltuples           relallvisible       reltoastrelid
## [13] relhasindex         relisshared         relpersistence
## [16] relkind             relnatts            relchecks
## [19] relhasoids          relhaspkey          relhasrules
## [22] relhastriggers      relhassubclass      relrowsecurity
```

```
## [25] relforcerowsecurity relispopulated      relreplident
## [28] relispartition      relfrozenxid        relminmxid
## [31] relacl              reloptions          relpartbound
## <0 rows> (or 0-length row.names)
```

This came from 14-sql_pet-examples-part-b.Rmd

```
rs1 <- DBI::dbGetQuery(con,
                "explain select r.*
                   from rental r
                 ;"
                )
head(rs1)
```

```
##                                                        QUERY PLAN
## 1 Seq Scan on rental r  (cost=0.00..310.44 rows=16044 width=36)
```

```
rs2 <- DBI::dbGetQuery(con,
                "explain select count(*) count
                   from rental r
                        left outer join payment p
                          on r.rental_id = p.rental_id
                    where p.rental_id is null
                 ;")
head(rs2)
```

```
##                                                                                QUERY PLAN
## 1                                     Aggregate  (cost=2086.78..2086.80 rows=1 width=8)
## 2                             ->  Merge Anti Join  (cost=0.57..2066.73 rows=8022 width=0)
## 3                                                 Merge Cond: (r.rental_id = p.rental_id)
## 4         ->  Index Only Scan using rental_pkey on rental r  (cost=0.29..1024.95 rows=16044 width=4)
## 5      ->  Index Only Scan using idx_fk_rental_id on payment p  (cost=0.29..819.23 rows=14596 width=4)
```

```
rs3 <- DBI::dbGetQuery(con,
                "explain select sum(f.rental_rate) open_amt,count(*) count
                   from rental r
                        left outer join payment p
                          on r.rental_id = p.rental_id
                        join inventory i
                          on r.inventory_id = i.inventory_id
                        join film f
                          on i.film_id = f.film_id
                    where p.rental_id is null
                 ;")
head(rs3)
```

```
##                                                                    QUERY PLAN
## 1                         Aggregate  (cost=2353.64..2353.65 rows=1 width=40)
## 2                  ->  Hash Join  (cost=205.14..2313.53 rows=8022 width=12)
## 3                                       Hash Cond: (i.film_id = f.film_id)
## 4                   ->  Hash Join  (cost=128.64..2215.88 rows=8022 width=2)
## 5                             Hash Cond: (r.inventory_id = i.inventory_id)
## 6               ->  Merge Anti Join  (cost=0.57..2066.73 rows=8022 width=4)
```

```
rs4 <- DBI::dbGetQuery(con,
                "explain select c.customer_id,c.first_name,c.last_name,sum(f.rental_rate) open_amt,coun
                   from rental r
                        left outer join payment p
```

```
                        on r.rental_id = p.rental_id
                      join inventory i
                        on r.inventory_id = i.inventory_id
                      join film f
                        on i.film_id = f.film_id
                      join customer c
                        on r.customer_id = c.customer_id
                where p.rental_id is null
                group by c.customer_id,c.first_name,c.last_name
                order by open_amt desc
               ;"
              )
head(rs4)
```

```
##                                                             QUERY PLAN
## 1                 Sort  (cost=2452.49..2453.99 rows=599 width=260)
## 2                              Sort Key: (sum(f.rental_rate)) DESC
## 3     ->  HashAggregate  (cost=2417.37..2424.86 rows=599 width=260)
## 4                                         Group Key: c.customer_id
## 5         ->  Hash Join  (cost=227.62..2357.21 rows=8022 width=232)
## 6                         Hash Cond: (r.customer_id = c.customer_id)
```

14.2 Clean up

```
# dbRemoveTable(con, "cars")
# dbRemoveTable(con, "mtcars")
# dbRemoveTable(con, "cust_movies")

# diconnect from the db
dbDisconnect(con)

sp_docker_stop("sql-pet")
```

```
## [1] "sql-pet"
```

Chapter 15

SQL queries behind the scenes (72)

Start up the `docker-pet` container

```
sp_docker_start("sql-pet")
```

now connect to the database with R

```
con <- sp_get_postgres_connection(user = Sys.getenv("DEFAULT_POSTGRES_USER_NAME"),
                         password = Sys.getenv("DEFAULT_POSTGRES_PASSWORD"),
                         dbname = "dvdrental",
                         seconds_to_test = 10)
```

15.1 SQL Execution Steps

- Parse the incoming SQL query
- Compile the SQL query
- Plan/optimize the data acquisition path
- Execute the optimized query / acquire and return data

```
dbWriteTable(con, "mtcars", mtcars, overwrite = TRUE)
rs <- dbSendQuery(con, "SELECT * FROM mtcars WHERE cyl = 4")
dbFetch(rs)
```

```
##     mpg cyl  disp  hp drat    wt  qsec vs am gear carb
## 1  22.8   4 108.0  93 3.85 2.320 18.61  1  1    4    1
## 2  24.4   4 146.7  62 3.69 3.190 20.00  1  0    4    2
## 3  22.8   4 140.8  95 3.92 3.150 22.90  1  0    4    2
## 4  32.4   4  78.7  66 4.08 2.200 19.47  1  1    4    1
## 5  30.4   4  75.7  52 4.93 1.615 18.52  1  1    4    2
## 6  33.9   4  71.1  65 4.22 1.835 19.90  1  1    4    1
## 7  21.5   4 120.1  97 3.70 2.465 20.01  1  0    3    1
## 8  27.3   4  79.0  66 4.08 1.935 18.90  1  1    4    1
## 9  26.0   4 120.3  91 4.43 2.140 16.70  0  1    5    2
## 10 30.4   4  95.1 113 3.77 1.513 16.90  1  1    5    2
## 11 21.4   4 121.0 109 4.11 2.780 18.60  1  1    4    2
```

```
dbClearResult(rs)
```

15.2 Passing values to SQL statements

```
#Pass one set of values with the param argument:
rs <- dbSendQuery(con,"SELECT * FROM mtcars WHERE cyl = 4")
dbFetch(rs)
```

```
##     mpg cyl  disp  hp drat    wt  qsec vs am gear carb
## 1  22.8   4 108.0  93 3.85 2.320 18.61  1  1    4    1
## 2  24.4   4 146.7  62 3.69 3.190 20.00  1  0    4    2
## 3  22.8   4 140.8  95 3.92 3.150 22.90  1  0    4    2
## 4  32.4   4  78.7  66 4.08 2.200 19.47  1  1    4    1
## 5  30.4   4  75.7  52 4.93 1.615 18.52  1  1    4    2
## 6  33.9   4  71.1  65 4.22 1.835 19.90  1  1    4    1
## 7  21.5   4 120.1  97 3.70 2.465 20.01  1  0    3    1
## 8  27.3   4  79.0  66 4.08 1.935 18.90  1  1    4    1
## 9  26.0   4 120.3  91 4.43 2.140 16.70  0  1    5    2
## 10 30.4   4  95.1 113 3.77 1.513 16.90  1  1    5    2
## 11 21.4   4 121.0 109 4.11 2.780 18.60  1  1    4    2
```

```
dbClearResult(rs)
```

15.3 Pass multiple sets of values with dbBind():

```
rs <- dbSendQuery(con, "SELECT * FROM mtcars WHERE cyl = $1")
dbBind(rs, list(6L)) # cyl = 6
dbFetch(rs)
```

```
##    mpg cyl  disp  hp drat    wt  qsec vs am gear carb
## 1 21.0   6 160.0 110 3.90 2.620 16.46  0  1    4    4
## 2 21.0   6 160.0 110 3.90 2.875 17.02  0  1    4    4
## 3 21.4   6 258.0 110 3.08 3.215 19.44  1  0    3    1
## 4 18.1   6 225.0 105 2.76 3.460 20.22  1  0    3    1
## 5 19.2   6 167.6 123 3.92 3.440 18.30  1  0    4    4
## 6 17.8   6 167.6 123 3.92 3.440 18.90  1  0    4    4
## 7 19.7   6 145.0 175 3.62 2.770 15.50  0  1    5    6
```

```
dbBind(rs, list(8L)) # cyl = 8
dbFetch(rs)
```

```
##     mpg cyl  disp  hp drat    wt  qsec vs am gear carb
## 1  18.7   8 360.0 175 3.15 3.440 17.02  0  0    3    2
## 2  14.3   8 360.0 245 3.21 3.570 15.84  0  0    3    4
## 3  16.4   8 275.8 180 3.07 4.070 17.40  0  0    3    3
## 4  17.3   8 275.8 180 3.07 3.730 17.60  0  0    3    3
## 5  15.2   8 275.8 180 3.07 3.780 18.00  0  0    3    3
## 6  10.4   8 472.0 205 2.93 5.250 17.98  0  0    3    4
## 7  10.4   8 460.0 215 3.00 5.424 17.82  0  0    3    4
## 8  14.7   8 440.0 230 3.23 5.345 17.42  0  0    3    4
## 9  15.5   8 318.0 150 2.76 3.520 16.87  0  0    3    2
## 10 15.2   8 304.0 150 3.15 3.435 17.30  0  0    3    2
## 11 13.3   8 350.0 245 3.73 3.840 15.41  0  0    3    4
## 12 19.2   8 400.0 175 3.08 3.845 17.05  0  0    3    2
## 13 15.8   8 351.0 264 4.22 3.170 14.50  0  1    5    4
## 14 15.0   8 301.0 335 3.54 3.570 14.60  0  1    5    8
```

```
dbClearResult(rs)
```

15.4 Clean up

```
# dbRemoveTable(con, "cars")
dbRemoveTable(con, "mtcars")
# dbRemoveTable(con, "cust_movies")

# diconnect from the db
dbDisconnect(con)

sp_docker_stop("sql-pet")
```

```
## [1] "sql-pet"
```

Chapter 16

Writing to the DBMS (73)

At the end of this chapter, you will be able to

- Write queries in R using docker container.
- Start and connect to the database with R.
- Create, Modify, and remove the table.

Start up the `docker-pet` container:

```
sp_docker_start("sql-pet")
```

Now connect to the database with R using your login info:

```
con <- sp_get_postgres_connection(user = Sys.getenv("DEFAULT_POSTGRES_USER_NAME"),
                         password = Sys.getenv("DEFAULT_POSTGRES_PASSWORD"),
                         dbname = "dvdrental",
                         seconds_to_test = 10)
```

16.1 Create a new table

This is an example from the DBI help file.

```
dbWriteTable(con, "cars", head(cars, 3)) # "cars" is a built-in dataset, not to be confused with mtcars

dbReadTable(con, "cars")   # there are 3 rows
```

```
##   speed dist
## 1     4    2
## 2     4   10
## 3     7    4
```

16.2 Modify an existing table

To add additional rows or instances to the "cars" table, we will use INSERT command with their values.

There are two different ways of adding values: list them or pass values using the param argument.

```
dbExecute(
  con,
```

```
  "INSERT INTO cars (speed, dist) VALUES (1, 1), (2, 2), (3, 3)"
)
```

```
## [1] 3
```

```
dbReadTable(con, "cars")   # there are now 6 rows
```

```
##   speed dist
## 1     4    2
## 2     4   10
## 3     7    4
## 4     1    1
## 5     2    2
## 6     3    3
```

```
# Pass values using the param argument:
dbExecute(
  con,
  "INSERT INTO cars (speed, dist) VALUES ($1, $2)",
  param = list(4:7, 5:8)
)
```

```
## [1] 4
```

```
dbReadTable(con, "cars")   # there are now 10 rows
```

```
##    speed dist
## 1      4    2
## 2      4   10
## 3      7    4
## 4      1    1
## 5      2    2
## 6      3    3
## 7      4    5
## 8      5    6
## 9      6    7
## 10     7    8
```

16.3 Remove table and Clean up

Here you will remove the table “cars”, disconnect from the database and exit docker.

```
dbRemoveTable(con, "cars")

# diconnect from the db
dbDisconnect(con)

sp_docker_stop("sql-pet")
```

```
## [1] "sql-pet"
```

Chapter 17

(APPENDIX) Appendix A: Other resources (89)

17.1 Editing this book

- Here are instructions for editing this tutorial

17.2 Docker alternatives

- Choosing between Docker and Vagrant

17.3 Docker and R

- Noam Ross' talk on Docker for the UseR and his Slides give a lot of context and tips.
- Good Docker tutorials
  - An introductory Docker tutorial
  - A Docker curriculum
- Scott Came's materials about Docker and R on his website and at the 2018 UseR Conference focus on **R inside Docker**.
- It's worth studying the ROpensci Docker tutorial

17.4 Documentation for Docker and Postgres

- The Postgres image documentation
- Dockerize PostgreSQL
- Postgres & Docker documentation
- Usage examples of Postgres with Docker

17.5 SQL and dplyr

- Why SQL is not for analysis but dplyr is
- Data Manipulation with dplyr (With 50 Examples)

17.6 More Resources

- David Severski describes some key elements of connecting to databases with R for MacOS users
- This tutorial picks up ideas and tips from Ed Borasky's Data Science pet containers, which creates a framework based on that Hack Oregon example and explains why this repo is named pet-sql.

Chapter 18

APPENDIX B - Mapping your local environment (92)

18.1 Environment Tools Used in this Chapter

Note that tidyverse, DBI, RPostgres, glue, and knitr are loaded. Also, we've sourced the [db-login-batch-code.R]('r-database-docker/book-src/db-login-batch-code.R') file which is used to log in to PostgreSQL.

library(rstudioapi)

The following code block defines Tool and versions for the graph that follows. The information order corresponds to the order shown in the graph.

```
library(DiagrammeR)

## OS information
os_lbl <- .Platform$OS.type
os_ver <- 0
if (os_lbl == 'windows') {
  os_ver <- system2('cmd',stdout = TRUE) %>%
    grep(x = .,pattern = 'Microsoft Windows \\[',value = TRUE) %>%
    gsub(x = .,pattern = "^Microsoft.+Version |\\]", replace = '')
}

if (os_lbl == 'unix' || os_lbl == 'Linux' || os_lbl == 'Mac') {
  os_ver <- system2('uname', '-r', stdout = TRUE)
}

## Command line interface into Docker Apps
## CLI/system2
cli <- array(dim = 3)
cli[1] <- "docker [OPTIONS] COMMAND ARGUMENTS\n\nsystem2(docker,[OPTIONS,]\n, COMMAND,ARGUMENTS)"
cli[2] <- 'docker exec -it sql-pet bash\n\nsystem2(docker,exec -it sql-pet bash)'
cli[3] <- 'docker exec -ti sql-pet psql -a \n-p 5432 -d dvdrental -U postgres\n\nsystem2(docker,exec -ti

# R Information
r_lbl       <- names(R.Version())[1:7]
r_ver       <- R.Version()[1:7]
```

```
# RStudio Information
rstudio_lbl <- c('RStudio version','Current program mode')
rstudio_ver <- c(as.character(rstudioapi::versionInfo()$version),rstudioapi::versionInfo()$mode)

# Docker Information
docker_lbl <- c('client version','server version')
docker_ver <- system2("docker", "version", stdout = TRUE) %>%
    grep(x = ., pattern = 'Version',value = TRUE) %>%
    gsub(x = ., pattern = ' +Version: +', replacement = '')

# Linux Information
linux_lbl <- 'Linux Version'
linux_ver <- system2('docker', 'exec -i sql-pet /bin/uname -r', stdout = TRUE)

# Postgres Information
con <- sp_get_postgres_connection(user = Sys.getenv("DEFAULT_POSTGRES_USER_NAME"),
                         password = Sys.getenv("DEFAULT_POSTGRES_PASSWORD"),
                         dbname = "dvdrental",
                         seconds_to_test = 10)

postgres_ver <- dbGetQuery(con,"select version()") %>%
  gsub(x = ., pattern = '\\(.*$', replacement = '')
```

The following code block uses the data generated from the previous code block as input to the subgraphs, the ones outlined in red. The application nodes are the parents of the subgraphs and are not outlined in red. The `Environment` application node represents the machine you are running the tutorial on and hosts the sub-applications.

Note that the '@@' variables are populated at the end of the `Environment` definition following the `## @@1 - @@5` source data comment.

```
grViz("
digraph Envgraph {

  # graph, node, and edge definitions
  graph [compound = true, nodesep = .5, ranksep = .25,
         color = red]

  node [fontname = Helvetica, fontcolor = darkslategray,
        shape = rectangle, fixedsize = true, width = 1,
        color = darkslategray]

  edge [color = grey, arrowhead = none, arrowtail = none]

  # subgraph for Environment information
  subgraph cluster1 {
    node [fixedsize = true, width = 3]
    '@@1-1'
  }

  # subgraph for R information
  subgraph cluster2 {
    node [fixedsize = true, width = 3]
    '@@2-1' -> '@@2-2' -> '@@2-3' -> '@@2-4'
```

```
    '@@2-4' -> '@@2-5' -> '@@2-6' -> '@@2-7'
  }

  # subgraph for RStudio information
  subgraph cluster3 {
    node [fixedsize = true, width = 3]
    '@@3-1' -> '@@3-2'
  }

  # subgraph for Docker information
  subgraph cluster4 {
    node [fixedsize = true, width = 3]
    '@@4-1' -> '@@4-2'
  }

  # subgraph for Docker-Linux information
  subgraph cluster5 {
    node [fixedsize = true, width = 3]
    '@@5-1'
  }

  # subgraph for Docker-Postgres information
  subgraph cluster6 {
    node [fixedsize = true, width = 3]
    '@@6-1'
  }

  # subgraph for Docker-Postgres information
  subgraph cluster7 {
    node [fixedsize = true, height = 1.25, width = 4.0]
    '@@7-1' -> '@@7-2' -> '@@7-3'
  }

  CLI [label='CLI\nRStudio system2',height = .75,width=3.0, color = 'blue' ]
  Environment             [label = 'Linux,Mac,Windows',width = 2.5]
  Environment -> R
  Environment -> RStudio
  Environment -> Docker

  Environment -> '@@1'    [lhead = cluster1] # Environment Information
  R           -> '@@2-1'  [lhead = cluster2] # R Information
  RStudio     -> '@@3'    [lhead = cluster3] # RStudio Information
  Docker      -> '@@4'    [lhead = cluster4] # Docker Information
  Docker      -> '@@5'    [lhead = cluster5] # Docker-Linux Information
  Docker      -> '@@6'    [lhead = cluster6] # Docker-Postgres Information

  '@@1' -> CLI
  CLI         -> '@@7'    [lhead = cluster7] # CLI
  '@@7-2'     -> '@@5'
  '@@7-3'     -> '@@6'
}
[1]: paste0(os_lbl,     ':\\n', os_ver)
[2]: paste0(r_lbl,      ':\\n', r_ver)
```

```
[3]: paste0(rstudio_lbl,':\\n', rstudio_ver)
[4]: paste0(docker_lbl, ':\\n', docker_ver)
[5]: paste0(linux_lbl,  ':\\n', linux_ver)
[6]: paste0('PostgreSQL:\\n', postgres_ver)
[7]: cli
")
```

One sub-application not shown above is your local console/terminal/CLI application. In the tutorial, fully constructed docker commands are printed out and then executed. If for some reason the executed docker command fails, one can copy and paste it into your local terminal window to see additional error information. Failures seem more prevalent in the Windows environment.

18.2 Communicating with Docker Applications

In this tutorial, the two main ways to interface with the applications in the Docker container are through the CLI or the RStudio `system2` command. The blue box in the diagram above represents these two interfaces.

Chapter 19

APPENDIX C - Creating the sql-pet Docker container a step at a time

Step-by-step Docker container setup with dvdrental database installed This needs to run *outside a project* to compile correctly because of the complexities of how knitr sets working directories (or because we don't really understand how it works!) The purpose of this code is to

- Replicate the docker container generated in Chapter 5 of the book, but in a step-by-step fashion
- Show that the `dvdrental` database persists when stopped and started up again.

19.1 Overview

Doing all of this in a step-by-step way that might be useful to understand how each of the steps involved in setting up a persistent PostgreSQL database works. If you are satisfied with the method shown in Chapter 5, skip this and only come back if you're interested in picking apart the steps.

```
library(tidyverse)
```

```
## -- Attaching packages ----------------------------------------------------------------------------------------

## v ggplot2 3.1.0     v purrr   0.2.5
## v tibble  1.4.2     v dplyr   0.7.7
## v tidyr   0.8.2     v stringr 1.3.1
## v readr   1.1.1     v forcats 0.3.0

## -- Conflicts ---------------------------------------------------------------------------------------------------
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(DBI)
library(RPostgres)
library(glue)
```

```
##
## Attaching package: 'glue'

## The following object is masked from 'package:dplyr':
##
##     collapse
```

```
require(knitr)
```

```
## Loading required package: knitr
```

```
library(dbplyr)
```

```
##
## Attaching package: 'dbplyr'
```

```
## The following objects are masked from 'package:dplyr':
##
##     ident, sql
```

```
library(sqlpetr)
library(here)
```

```
## here() starts at /Users/jds/Documents/Library/R/r-system/sql-pet
```

19.2 Download the `dvdrental` backup file

The first step is to get a local copy of the `dvdrental` PostgreSQL **restore file**. It comes in a zip format and needs to be un-zipped.

```
opts_knit$set(root.dir = normalizePath('../'))
if (!require(downloader)) install.packages("downloader")
```

```
## Loading required package: downloader
```

```
library(downloader)

download("http://www.postgresqltutorial.com/wp-content/uploads/2017/10/dvdrental.zip", destfile = glue(

unzip("dvdrental.zip", exdir = here()) # creates a tar archhive named "dvdrental.tar"
```

Check on where we are and what we have in this directory:

```
dir(path = here(), pattern = "^dvdrental(.tar|.zip)")
```

```
## [1] "dvdrental.tar" "dvdrental.zip"
```

```
sp_show_all_docker_containers()
```

```
## [1] "CONTAINER ID      IMAGE             COMMAND               CREATED          STATUS                PORTS
## [2] "3fea949dfb09      postgres-dvdrental  \"docker-entrypoint.s…\"  About a minute ago  Exited (0) 6 se
```

Remove the `sql-pet` container if it exists (e.g., from a prior run)

```
if (system2("docker", "ps -a", stdout = TRUE) %>%
    grepl(x = ., pattern = 'sql-pet') %>%
    any()) {
  sp_docker_remove_container("sql-pet")
}
```

```
## [1] "sql-pet"
```

19.3 Build the Docker Container

Build an image that derives from postgres:10. Connect the local and Docker directories that need to be shared. Expose the standard PostgreSQL port 5432.

```
wd <- here()
wd
```

```
## [1] "/Users/jds/Documents/Library/R/r-system/sql-pet"
```

```
docker_cmd <- glue(
  "run ",      # Run is the Docker command.  Everything that follows are `run` parameters.
  "--detach ", # (or `-d`) tells Docker to disconnect from the terminal / program issuing the command
  " --name sql-pet ",     # tells Docker to give the container a name: `sql-pet`
  "--publish 5432:5432 ", # tells Docker to expose the Postgres port 5432 to the local network with 543
  "--mount ", # tells Docker to mount a volume -- mapping Docker's internal file structure to the host
  'type=bind,source="', wd, '",target=/petdir',
  " postgres:10 " # tells Docker the image that is to be run (after downloading if necessary)
)

docker_cmd
```

```
## run --detach  --name sql-pet --publish 5432:5432 --mount type=bind,source="/Users/jds/Documents/Library
```

```
system2("docker", docker_cmd, stdout = TRUE, stderr = TRUE)
```

```
## [1] "251c3b371b6e7e1ae7b2e4ec10ad2f518d23690065ada00b22afa10066426f06"
```

Peek inside the docker container and list the files in the `petdir` directory. Notice that `dvdrental.tar` is in both.

```
# local file system:
dir(path = here(), pattern = "^dvdrental.tar")
```

```
## [1] "dvdrental.tar"
```

```
# inside docker
system2('docker', 'exec sql-pet ls petdir | grep "dvdrental.tar" ',
        stdout = TRUE, stderr = TRUE)
```

```
## [1] "dvdrental.tar"
```

```
Sys.sleep(3)
```

19.4 Create the database and restore from the backup

We can execute programs inside the Docker container with the `exec` command. In this case we tell Docker to execute the `psql` program inside the `sql-pet` container and pass it some commands as follows.

```
sp_show_all_docker_containers()
```

```
## [1] "CONTAINER ID      IMAGE           COMMAND                CREATED          STATUS           PORTS
## [2] "251c3b371b6e      postgres:10      \"docker-entrypoint.s…\"  4 seconds ago     Up 3 seconds      0.
```

inside Docker, execute the postgress SQL command-line program to create the dvdrental database:

```
system2('docker', 'exec sql-pet psql -U postgres -c "CREATE DATABASE dvdrental;"',
        stdout = TRUE, stderr = TRUE)
```

```
## [1] "CREATE DATABASE"
```

```
Sys.sleep(3)
```

The `psql` program repeats back to us what it has done, e.g., to create a database named `dvdrental`. Next we execute a different program in the Docker container, `pg_restore`, and tell it where the restore file is located. If successful, the `pg_restore` just responds with a very laconic `character(0)`. restore the database from the .tar file

```
system2("docker", "exec sql-pet pg_restore -U postgres -d dvdrental petdir/dvdrental.tar", stdout = TRUE
```

```
## character(0)
```

```
Sys.sleep(3)
```

19.5 Connect to the database with R

If you are interested take a look inside the `sp_get_postgres_connection` function to see how the DBI package is beingcused.

```
con <- sp_get_postgres_connection(user = Sys.getenv("DEFAULT_POSTGRES_USER_NAME"),
                                  password = Sys.getenv("DEFAULT_POSTGRES_PASSWORD"),
                                  dbname = "dvdrental",
                                  seconds_to_test = 20)

dbListTables(con)
```

```
##  [1] "actor_info"                 "customer_list"
##  [3] "film_list"                  "nicer_but_slower_film_list"
##  [5] "sales_by_film_category"     "staff"
##  [7] "sales_by_store"             "staff_list"
##  [9] "category"                   "film_category"
## [11] "country"                    "actor"
## [13] "language"                   "inventory"
## [15] "payment"                    "rental"
## [17] "city"                       "store"
## [19] "film"                       "address"
## [21] "film_actor"                 "customer"
```

```
dbDisconnect(con)

# Stop and start to demonstrate persistence
```

Stop the container

```
sp_docker_stop("sql-pet")
```

```
## [1] "sql-pet"
```

Restart the container and verify that the dvdrental tables are still there

```
sp_docker_start("sql-pet")

con <- sp_get_postgres_connection(user = Sys.getenv("DEFAULT_POSTGRES_USER_NAME"),
                                  password = Sys.getenv("DEFAULT_POSTGRES_PASSWORD"),
                                  dbname = "dvdrental",
                                  seconds_to_test = 10)
dbListTables(con)
```

```
##  [1] "actor_info"                 "customer_list"
##  [3] "film_list"                  "nicer_but_slower_film_list"
##  [5] "sales_by_film_category"     "staff"
##  [7] "sales_by_store"             "staff_list"
##  [9] "category"                   "film_category"
## [11] "country"                    "actor"
## [13] "language"                   "inventory"
## [15] "payment"                    "rental"
## [17] "city"                       "store"
## [19] "film"                       "address"
## [21] "film_actor"                 "customer"
```

19.6 Cleaning up

It's always good to have R disconnect from the database

```
dbDisconnect(con)
```

Stop the container and show that the container is still there, so can be started again.

```
sp_docker_stop("sql-pet")
```

```
## [1] "sql-pet"
```

show that the container still exists even though it's not running

```
sp_show_all_docker_containers()
```

```
## [1] "CONTAINER ID      IMAGE          COMMAND                CREATED          STATUS                     POR
## [2] "251c3b371b6e      postgres:10      \"docker-entrypoint.s…\"  14 seconds ago     Exited (0) Less thar
```

We are leaving the `sql-pet` container intact so it can be used in running the rest of the examples and book.

Clean up by removing the local files used in creating the database:

```
file.remove(here("dvdrental.zip"))
```

```
## [1] TRUE
```

```
file.remove(here("dvdrental.tar"))
```

```
## [1] TRUE
```

Chapter 20

APPENDIX D - Quick Guide to SQL (94)

SQL stands for Structured Query Language. It is a database language where we can perform certain operations on the existing database and we can use it create a new database. There are four main categories where the SQL commands fall into: DDL, DML, DCL, and TCL.

##Data Definition Langauge (DDL)

It consists of the SQL commands that can be used to define database schema. The DDL commands include:

1. `CREATE`
2. `ALTER`
3. `TRUNCATE`
4. `COMMENT`
5. `RENAME`
6. `DROP`

##Data Manipulation Langauge (DML)

These four SQL commands deals with the manipulation of data in the database.

1. `SELECT`
2. `INSERT`
3. `UPDATE`
4. `DELETE`

##Data Control Language (DCL)

The DCL commands deals with user's rights, permissions and other controls in database management system.

1. `GRANT`
2. `REVOKE`

##Transaction Control Language (TCL)

These commands deals with the control over transaction within the database. Transaction combines a set of tasks into single execution.

1. `SET TRANSACTION`
2. `SAVEPOINT`
3. `ROLLBACK`
4. `COMMIT`

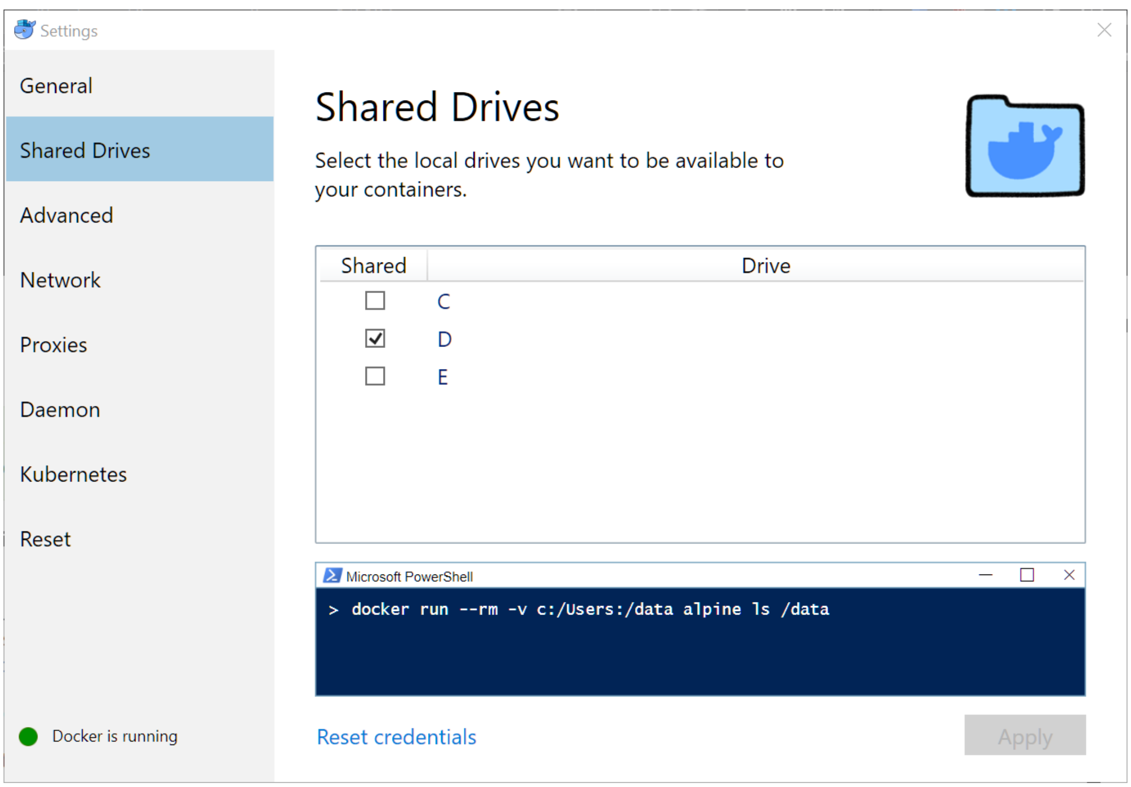
Chapter 21

Additional technical details for Windows users (95)

21.1 Docker for Windows settings

21.1.1 Shared drives

If you're going to mount host files into container file systems (as we do in the following chapters), you need to set up shared drives. Open the Docker settings dialog and select `Shared Drives`. Check the drives you want to share. In this screenshot, the `D:` drive is my 1 terabyte hard drive.

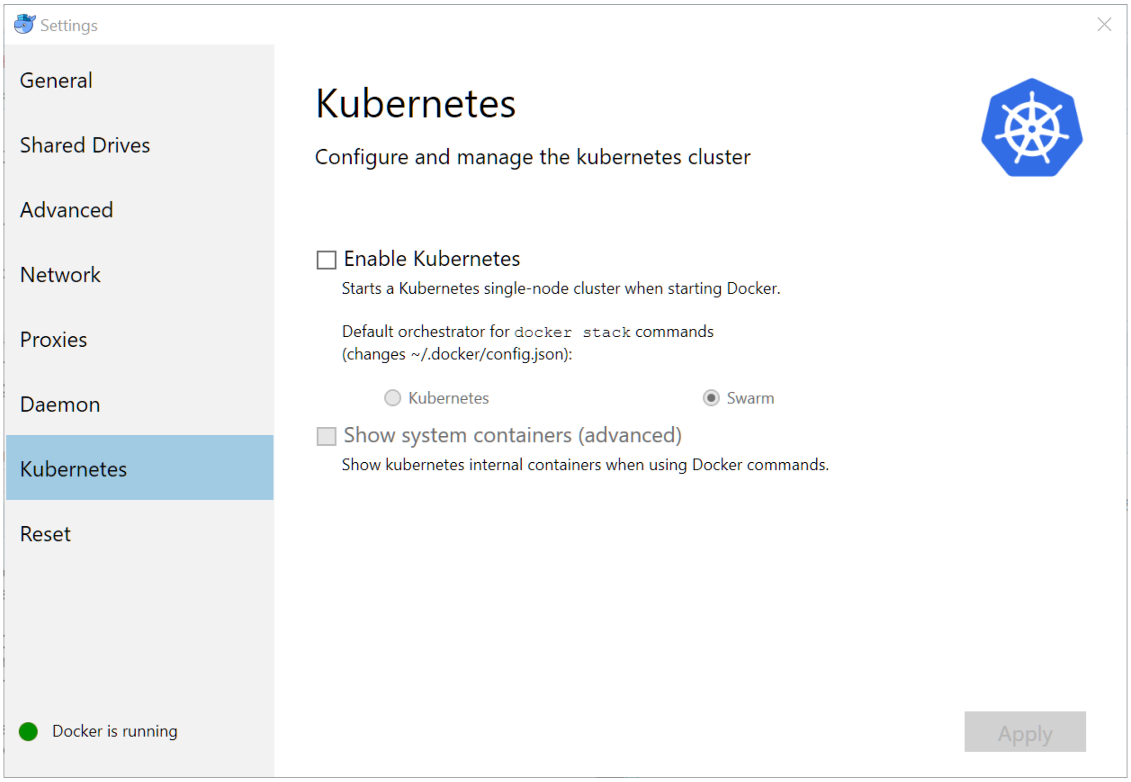


21.1.2 Kubernetes

Kubernetes is a container orchestration / cloud management package that's a major DevOps tool. It's heavily supported by Red Hat and Google, and as a result is becoming a required skill for DevOps.

However, it's overkill for this project at the moment. So you should make sure it's not enabled.

Go to the `Kubernetes` dialog and make sure the `Enable Kubernetes` checkbox is cleared.



21.2 Git, GitHub and line endings

Git was originally developed for Linux - in fact, it was created by Linus Torvalds to manage hundreds of different versions of the Linux kernel on different machines all around the world. As usage has grown, Git has achieved a huge following and is the version control system used by most large open source projects, including this one.

If you're on Windows, there are some things about Git and GitHub you need to watch. First of all, there are quite a few tools for running Git on Windows, but the RStudio default and recommended one is Git for Windows (https://git-scm.com/download/win).

By default, text files on Linux end with a single linefeed (`\n`) character. But on Windows, text files end with a carriage return and a line feed (`\r\n`). See https://en.wikipedia.org/wiki/Newline for the gory details.

Git defaults to checking files out in the native mode. So if you're on Linux, a text file will show up with the Linux convention, and if you're on Windows, it will show up with the Windows convention.

Most of the time this doesn't cause any problems. But Docker containers usually run Linux, and if you have files from a repository on Windows that you've sent to the container, the container may malfunction or give weird results. *This kind of situation has caused a lot of grief for contributors to this project, so beware.*

In particular, executable `sh` or `bash` scripts will fail in a Docker container if they have Windows line endings. You may see an error message with `\r` in it, which means the shell saw the carriage return (`\r`) and gave up.

But often you'll see no hint at all what the problem was.

So you need a way to tell Git that some files need to be checked out with Linux line endings. See https://help.github.com/articles/dealing-with-line-endings/ for the details. Summary:

1. You'll need a `.gitattributes` file in the root of the repository.
2. In that file, all text files (scripts, program source, data, etc.) that are destined for a Docker container will need to have the designator `<spec> text eol=lf`, where `<spec>` is the file name specifier, for example, `*.sh`.

This repo includes a sample: .gitattributes