

# **Mastering Health Data Science Using R**

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# Mastering Health Data Science Using R

This book serves as an interactive introduction to R for public health and health data science students. Topics include data structures in R, exploratory analysis, distributions, hypothesis testing, and regression analysis. The presentation assumes knowledge with the underlying methodology and focuses instead on how to use R to implement your analysis.

This book is written using Jupyter Book. You can download each chapter as a Jupyter notebook or pdf directly from the chapter page or download a corresponding R Markdown file from the [github repository](#). Alternatively, you can open each notebook using Binder to directly run the code you see in the text and to test out your solutions to the exercises included. If this is your first time learning R or you are unfamiliar with Jupyter notebooks or R Markdown, we encourage you to start with [Chapter 1: Intro to R, RStudio, and Jupyter](#) to get a tour on how to use these tools. The github repository also contains a few [cheat sheets](#) including a pdf containing [all functions](#) shown in this book.

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# **Part I**

## **Introduction to R**

# 1 Getting Started with R

This chapter will introduce you to R as a programming language and show you how we can use this language in different ways: directly through the [R console](#), using [RStudio](#), and using [Jupyter Notebooks](#).

## 1.1 Why R?

What are some of the benefits of using R?

- R is built for statisticians and data analysts.
- R is open source.
- R has most of the latest statistical methods available.
- R is flexible.

Since R is built for statisticians, it is built with data in mind. This comes in handy when we want to streamline how we process and analyze data. It also means that many statisticians working on new methods are publishing user-created packages in R, so R users have access to most methods of interest. R is also an interpreted language, which means that we do not have to compile our code into machine language first: this allows for simpler syntax and more flexibility when writing our code, which also makes it a great first programming language to learn.

Python is another interpreted language often used for data analysis. Both languages feature simple and flexible syntax, but while python is more broadly developed for usage outside of data science and statistical analyses, R is a great programming language for those in health data science. I use both languages and find switching between them to be straightforward, but I do prefer R for anything related to data or statistical analysis.

### 1.1.1 Installation of R and RStudio

To run R on your computer, you will need to [download and install R](#). This will allow you to open the R application and run R code interactively. However, to get the most out of programming with R, you will want to install RStudio, which is an integrated development environment (IDE) for R and python. RStudio offers a nice environment for writing, editing, running, and debugging R code. We will talk through more of the benefits of using RStudio below.

Each chapter in this book is written as a Jupyter notebook but can also be downloaded as an R markdown file. You can open R Markdown files in RStudio to run the code as you read and complete the practice questions and exercises. Alternatively, at the top of these pages, you can open each of these chapters as a Jupyter notebook through Binder. This will open an interactive, online session for you to run the R code. We recommend this option for the best viewing and learning experience, though if you would like to run the Jupyter notebooks on your own machine, you will need to install [Jupyter](#) and the associated [R kernel](#).

## 1.2 The R Console

The R console provides our first intro to code in R. The image below shows what the console will look like when you open it. You should see a blinking cursor - this where we can write our first line of code!

To start, type `2+3` and press ENTER. You should see that 5 is printed below that code and that your cursor is moved to the next line.

### 1.2.1 Basic Computations and Objects

In the example above, we coded a simple addition. Try out some other basic calculations using the operators below:

- Addition: `5+6`
- Subtraction: `7-2`
- Multiplication: `2*3`
- Division: `6/3`
- Exponentiation: `4^2`
- Modulo: `100 %% 4`

For example, use the modulo operator to find what  $100 \bmod 4$  is. It should return 0 since 100 is divisible by 4.

If we want to save the result of any computation, we need to create an object to store our value of interest. An **object** is simply a named data structure that allows us to reference that data structure. Objects are also commonly called **variables**. In the code below, we create an object **x** which stores the value 5 using the assignment operator `<-`. The assignment operator assigns whatever is on the right hand side of the operator to the name on the left hand side. We can now reference **x** by calling its name. Additionally, we can update its value by adding 1. In the second line of code, the computer first finds the value of the right hand side by finding the current value of **x** before adding 1 and assigning it back to **x**.

```
x <- 2+3
x <- x+1
x
#> [1] 6
```

We can create and store multiple objects by using different names. The code below creates a new object **y** that is one more than the value of **x**. We can see that the value of **x** is still 5 after running this code.

```
x <- 2+3
y <- x
y <- y + 1
x
#> [1] 5
```

### 1.2.2 Naming Conventions

As we start creating objects, we want to make sure we use good object names. Here are a few tips for naming objects effectively:

- Stick to a single format. We will use **snake\_case**, which uses underscores between words (e.g. `my_var`, `class_year`).
- Make your names useful. Try to avoid using names that are too long (e.g. `which_day_of_the_week`) or do not contain enough information (e.g., `x1`, `x2`, `x3`).
- Replace unexplained values with an object. For example, if you need to do some calculations using 100 as the number of participants, create an object `n_part` with value 100 rather than repeatedly using the number. This makes the code easy to update and helps the user avoid possible errors.

## 1.3 RStudio and R Markdown

If we made a mistake in the code above, we would have to retype everything from the beginning. However, when we write code, we often want to be able to run it multiple times and develop it in stages. R scripts and R markdown files allow us to save all of our R code in files that we can update and re-run, which allows us to create reproducible and shareable analyses. We will now move to RStudio as our development environment to demonstrate creating an R script. When you open RStudio, you will see multiple windows. Start by opening a new R file by going to File -> New File -> R Script. You should now see several windows.

In the code editor window in the top left, add the following code to your .R file and save the file. Note that here we used snake\_case to name our objects!

```
# Calculate student to faculty ratio, 2023 enrollment
num_students <- 132
num_faculty <- 23
student_fac_ratio <- num_students/num_faculty
```

The first line starts with # and does not contain any code. This is a comment line, which allows us to add context, intent, or extra information to help the reader understand our code. A good rule of thumb is that we want to write enough comments so that we could open our code in six months and be able to understand what we were doing. As we develop longer chunks of code, this will become more important.

### 1.3.1 Video Tour of RStudio and R Markdown

In order to run the code in the script, we need to tell RStudio we are ready to run it. The video below shows you how to run a script and gives a tour of the other windows you see in RStudio. It will also introduce you to R Markdown files, which integrate text and code together. As we described above, each chapter in this book can be downloaded as a corresponding R Markdown file.

<https://www.youtube.com/embed/WoGbZnkiQEM>

### 1.3.2 Calling Functions

When we use R, we have access to all the functions available in base R. A **function** takes in one or more inputs and returns a single output object. Let's first use the simple function `exp()`. This exponential function takes in one (or more) numeric values and exponentiates them. The code below computes  $e^3$ .

```
exp(3)  
#> [1] 20.1
```

Some other simple functions are shown below that all convert a numeric input to an integer value. The `ceiling()` and `floor()` functions returns the ceiling and floor of your input, and the `round()` function will round your input to the closest integer. Note that the `round()` function will round a 5 to the closest even integer.

```
ceiling(3.7)  
#> [1] 4
```

```
floor(3.7)  
#> [1] 3
```

```
round(2.5)  
#> [1] 2  
round(3.5)  
#> [1] 4
```

If we want to learn about a function, we can use the help operator `?` by typing it in front of the function you are interested in: this will bring up the documentation for that particular function. This documentation will often tell you the usage of the function, the **arguments** (the object inputs), the **value** (information about the returned object), and will give some examples of how to use the function. For example, if we want to understand the difference between `floor()` and `ceiling()`, we can call `?floor` and `?ceiling`. This should bring up the documentation in your help window. We can then read that the floor function rounds a numeric input down to the nearest integer whereas the ceiling function rounds a numeric input up to the nearest integer.

### 1.3.3 Working Directories and Paths

Let's try using another example function: `read.csv()`. This function reads in a comma-delimited file and returns the information as a data frame (try typing `?read.csv` in the console to read more about this function). We will learn more about data frames in Chapter 2. The first argument to this function is a file, which can be expressed as either a filename or a path to a file. First, download the file `fake_names.csv` from this book's [github repository](#). By default, R will look for the file in your current working directory. To find the working directory, you can run `getwd()`. You can see below that my current working directory is where the book content is on my computer.

```
getwd()  
#> [1] "/Users/Alice/Dropbox/health-data-science-in-r/book"
```

You can either move the .csv file to your current working directory and load it in, or you can specify the path to the .csv file. Another option is to update your working directory by using the `setwd()` function (e.g. `setwd('/Users/Alice/Dropbox/health-data-science-using-r/book/data')`). If you receive an error that a file cannot be found, you most likely have the wrong path to the file or the wrong file name. Below, I chose to specify the path to the downloaded .csv file, saved this file to an object called `df`, and then printed that `df` object.

```
df <- read.csv("data/fake_names.csv") # update this with the path to your file  
df  
#>          Name Age      DOB            City State  
#> 1        Ken Irwin 37 6/28/85 Providence    RI  
#> 2 Delores Whittington 56 4/28/67 Smithfield    RI  
#> 3 Daniel Hughes 41 5/22/82 Providence    RI  
#> 4     Carlos Fain 83 2/2/40 Warren        RI  
#> 5     James Alford 67 2/23/56 East Providence RI  
#> 6     Ruth Alvarez 34 9/22/88 Providence    RI
```

We can see that `df` contains the information from the .csv file and that R has printed the first few observations of the data.

### 1.3.4 Installing and Loading Packages

When working with data frames, we will often use the `tidyverse` package (<https://www.tidyverse.org/>), which is actually a collection of R packages for data science applications. An R package is a collection of functions and/or sample data that allow us to expand on the functionality of R beyond the base functions. You can check whether you have the `tidyverse` package installed by going to the package pane in RStudio or by running the command below, which will display all your installed packages.

```
installed.packages()
```

If you don't already have a package installed, you can install it using the `install.packages()` function. Note that you have to include single or double quotes around the package name when using this function. You only have to install a package one time.

```
install.packages('tidyverse')
```

The function `read_csv()` is another function to read in comma-delimited files that is part of the `readr` package in the `tidyverse`. However, if we tried to use this function to load in our data, we would get an error that the function cannot be found. That is because we haven't loaded

in this package. To do so, we use the `library()` function. Unlike the `install.packages()` function, we do not have to use quotes around the package name when calling this `library()` function. When we load in a package, we will see some messages. For example, below we see that this package contains the functions `filter()` and `lag()` that are also functions in base R. In future chapters, we will suppress these messages to make the chapter presentation nicer. After loading the tidyverse package, we can now use the `read_csv()` function as shown below.

```
library(tidyverse)
#> -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
#> v dplyr     1.1.3     v readr      2.1.4
#> v forcats   1.0.0     v stringr    1.5.0
#> v ggplot2   3.4.4     v tibble     3.2.1
#> v lubridate  1.9.2     v tidyverse  1.3.0
#> v purrr     1.0.1
#> -- Conflicts ----- tidyverse_conflicts() --
#> x dplyr::filter() masks stats::filter()
#> x dplyr::lag()   masks stats::lag()
#> i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to

df <- read_csv("data/fake_names.csv", show_col_types=FALSE)
df
#> # A tibble: 6 x 5
#>   Name           Age DOB     City       State
#>   <chr>        <dbl> <chr>    <chr>
#> 1 Ken Irwin     37 6/28/85 Providence RI
#> 2 Delores Whittington 56 4/28/67 Smithfield RI
#> 3 Daniel Hughes 41 5/22/82 Providence RI
#> 4 Carlos Fain   83 2/2/40 Warren     RI
#> 5 James Alford  67 2/23/56 East Providence RI
#> # i 1 more row
```

Alternatively, we could have told R where to locate the function by adding `readr::` before the function. This tells it to find `read_csv` function in the `readr` package. This can be helpful even if we have already loaded in the package, since sometimes multiple packages have functions with the same name.

```
df <- readr::read_csv("data/fake_names.csv", show_col_types = FALSE)
```

### 1.3.5 RStudio Global Options

You have now had a basic tour of RStudio. Before we transition to introducing Jupyter Notebooks, take a look at your Global Options (under Tools). We highly recommend that you update your RStudio options to not save your workspace on exiting or load it on starting. This will ensure that you create fully reproducible code and avoid possible errors or confusion.

## 1.4 Jupyter Notebooks

Jupyter notebooks are an alternative way to edit and share code. Each chapter of this book was created using a Jupyter notebook, and these notebooks are the best way to interact with the content. Similar to R Markdown, a Jupyter notebook allows us to intersperse code and text. However, this is done using individual cells that are either markdown (text) or code. Each of these cells can be run alone without us having to compile the full notebook. Jupyter notebooks can also be created using julia, python, or R (hence the name ju-pyt-er).

### 1.4.1 Video Tour of Jupyter Notebooks and Binder

At the top of this chapter is a rocket button to open this Notebook using Binder. Binder creates an online computational environment to host your notebooks that already has all the R packages you'll need for this book installed, which is the easiest way to interact with the content in this book. Click that link to open this chapter and then view the video below to see how to use this feature when reading this book.

<https://www.youtube.com/embed/aZbvJc5w5Og>

## 1.5 Tips and Reminders

We end this chapter with some final tips and reminders.

- **Keyboard Shortcuts:** Both RStudio and Jupyter notebooks have useful keyboard shortcuts that will make your programming experience more streamlined. It is worth getting familiar with some of the most common keyboard shortcuts - here are some helpful cheatsheets for keyboard shortcuts in [Jupyter Notebooks](#) and in [RStudio](#).
- **Asking for help:** Within R, you can use the `? operator` or the `help()` function to pull up documentation on a given function. This documentation is also available [online](#).
- **Finding all objects:** You can use the Environment panel or `ls()` function to find all current objects. If you have an error that an object you are calling does not exist, take a look to find where you defined it.

- **Checking packages:** If you get an error that a function does not exist, check to make sure you have loaded that package using the `library` function. The list of packages used in this book is given on the [github repository homepage](#).

# 2 Data Structures in R

In this chapter, we will demonstrate the key **data structures** in R. Data structures are how information is stored in R, and the data structures that we use inform R how to interpret our code. Any **object** is a named instance of a data structure. For example, the object `ex_num` below is a vector of numeric type.

```
ex_num <- 4
```

The main data structures in R are **vectors**, **factors**, **matrices**, **arrays**, **lists**, and **data frames**. These structures are distinguished by their dimensions and by the type of data they store. For example, we might have a 1-dimensional vector that contains all numeric values, or we could have a 2-dimensional data frame with rows and columns where we might have one numeric column and one character column. In the image below, there are two vectors with different types (character and numeric) on top and then a matrix and data frame below. In this chapter, we will cover each data structure except for arrays. Arrays are an extension of matrices that allow for data that is more than 2-dimensional and are not needed for the applications covered in this book.

## 2.1 Data Types

Each individual value in R has a type: **logical**, **integer**, **double**, or **character**. We can think of these as the building blocks of all data structures. Below, we can use the `typeof()` function to find the type of our vector from above, which shows that the value of `ex_num` is a **double**. A double is a numeric value with a stored decimal.

```
typeof(ex_num)
#> [1] "double"
```

On the other hand, an **integer** is a whole number that does not contain a decimal. We now create an integer object `ex_int`. To indicate to R that we want to restrict our values to integer values, we use an L after the number.

```
ex_int <- 4L
typeof(ex_int)
#> [1] "integer"
```

Both `ex_num` and `ex_int` are numeric objects, but we can also work with two other types of objects: **characters** (e.g. “php”, “stats”) and **booleans** (e.g. TRUE, FALSE), also known as **logicals**.

```
ex_bool <- TRUE
ex_char <- "Alice"

typeof(ex_bool)
#> [1] "logical"
typeof(ex_char)
#> [1] "character"
```

One important characteristic of logical objects is that R will also interpret them as 0/1. This means they can be added as in the example below: each TRUE has a value of 1 and each FALSE has a value of 0.

```
TRUE+FALSE+TRUE
#> [1] 2
```

To create all of the above objects, we used the assignment operator `<-`, which we discussed in Chapter 1. You may see code elsewhere that uses an `=` instead. While `=` can also be used for assignment, it is more standard practice to use `<-`.

## 2.2 Vectors

In the examples above, we created objects with a single value. R actually uses a vector of length 1 to store this information. **Vectors** are 1-dimensional data structures that can store multiple data values of the same type (e.g. character, boolean, or numeric).

We can confirm this by using the `is.vector()` function, which returns whether or not the inputted argument is a vector.

```
is.vector(ex_bool)
#> [1] TRUE
```

One way to create a vector with multiple values is to use the combine function `c()`. Below we create two vectors: one with the days of the week and one with the amount of rain on each day. The first vector has all character values, and the second one has all numeric values.

```
days <- c("Monday", "Tuesday", "Wednesday", "Thursday", "Friday")
rain <- c(5, 0.1, 0, 0, 0.4)
```

Remember, vectors cannot store objects of different types. Because of this, in the code below, R automatically converts the numeric value to be a character in order to store these values in a vector together.

```
c("Monday", 5)
#> [1] "Monday" "5"
```

The `class()` function returns the data structure of an object. If we check the classes of these two objects using the `class()` function, we will see that R tells us that the first is a character vector and the second is a numeric vector. This matches the data type in this case.

```
class(days)
#> [1] "character"
class(rain)
#> [1] "numeric"
```

What happens when we create an empty vector? What is the class?

```
ex_empty <- c()
class(ex_empty)
#> [1] "NULL"
```

In this case, there is no specified type yet. If we wanted to specify the type, we could make an empty vector using the `vector()` function.

```
ex_empty <- vector(mode = "numeric")
class(ex_empty)
#> [1] "numeric"
```

Another way to create a vector is with the `rep()` or `seq()` functions. The first function `rep(x, times)` takes in a vector `x` and a number of times `times` and outputs `x` repeated that many times. Let's try this with a single value below. The second function `seq(from, to, step)` takes in a numeric starting value `from`, end value `to`, and step size `step` and returns a sequence from `from` in increments of `step` until a maximum value of `to` is reached.

```

rep(0, 5)
#> [1] 0 0 0 0 0
rep("Monday", 4)
#> [1] "Monday" "Monday" "Monday" "Monday"
seq(1, 5, 1)
#> [1] 1 2 3 4 5
seq(0, -10, -2)
#> [1] 0 -2 -4 -6 -8 -10

```

### 2.2.1 Indexing a Vector

Once we have a vector, we may want to access certain values stored in that vector. To do so, we index the vector using the position of each value: the first value in the vector has index 1, the second value has index 2, etc. When we say a vector is 1-dimensional, we mean that we can define the position of each value by a single index. To index the vector, we then use square brackets [] after the vector name and provide the position. Below, we use these indices to find the value at index 1 and the value at index 4.

```

days[1]
#> [1] "Monday"
days[4]
#> [1] "Thursday"

```

We can either access a single value or a subset of values using a vector of indices. Let's see what happens when we use a vector of indices `c(1,4)` and then try using `-c(1,4)` and see what happens then. In the first case, we get the values at index 1 *and* at index 4. In the second case, we get all values *except* at those indices. The - indicates that we want to remove rather than select these indices.

```

days[c(1,4)]
#> [1] "Monday"    "Thursday"
days[-c(1,4)]
#> [1] "Tuesday"   "Wednesday" "Friday"

```

However, always indexing by the index value can sometimes be difficult or inefficient. One extra feature of vectors is that we can associate a name with each value. Below, we update the names of the vector `rain` to be the days of the week and then find Friday's rain count by indexing with the name.

```

names(rain) <- days
print(rain)
#>     Monday   Tuesday Wednesday Thursday      Friday
#>     5.0       0.1       0.0       0.0       0.4
rain["Friday"]
#> Friday
#> 0.4

```

The last way to index a vector is to use TRUE and FALSE values. If we have a vector of booleans that is the same length as our original vector, then this will return all the values that correspond to a TRUE value. For example, indexing the `days` vector by the logical vector `ind_bools` below will return its first and fourth values. We will see more about using logic to access certain values later on.

```

ind_bools <- c(TRUE, FALSE, FALSE, TRUE, FALSE)
days[ind_bools]
#> [1] "Monday"    "Thursday"

```

## 2.2.2 Editing a Vector and Calculations

The mathematical operators we saw in the last chapter (`+`, `-`, `*`, `/`, `^`, `%%`) can all be applied to numeric vectors and will be applied element-wise. That is, in the code below, the two vectors are added together by index. This holds true for some of the built-in math functions as well:

- `exp()` - exponential
- `log()` - log
- `sqrt()` - square root
- `abs()` - absolute value
- `round()` - round to nearest integer value
- `ceiling()` - round up to the nearest integer value
- `floor()` - round down to the nearest integer value

```

c(1,2,3) + c(1,1,1)
#> [1] 2 3 4
c(1,2,3) + 1 # equivalent to the code above
#> [1] 2 3 4
sqrt(c(1,4,16))
#> [1] 1 2 4

```

After we create a vector, we may need to update its values. For example, we may want to change a specific value. We can do so using indexing. Below, we update the rain value for Friday using the assignment operator.

```
rain["Friday"] <- 0.5
rain
#>   Monday   Tuesday Wednesday Thursday     Friday
#>       5.0        0.1       0.0       0.0       0.5
```

Further, we may need to add extra entries. We can do so using the `c()` function again but this time passing in the vector we want to add to as our first argument. This will create a single vector with all previous and new values. Below, we add two days to both vectors and then check the length of the updated vector `rain`. The `length()` function returns the length of a vector.

```
length(rain)
#> [1] 5
days <- c(days, "Saturday", "Sunday") # add the weekend with no rain
rain <- c(rain, 0, 0)
length(rain)
#> [1] 7
```

We can also call some useful functions on vectors. For example, the `sum()`, `max()`, and `min()` functions will return the sum, maximum value, and minimum value of a vector, respectively.

### 2.2.3 Practice Question

Create a vector of the odd numbers from 1 to 11 using the `seq()` function. Then, find the third value in the vector using indexing, which should have value 5.

```
# Insert your solution here:
```

### 2.2.4 Common Vector Functions

Below we list some of the most common vector functions that are available in base R. All of these functions assume that the vector is numeric. If we pass the function a logical vector, R will convert the vector to 0/1 first, and if we pass the function a character vector, R will give us an error message.

- `sum()` - summation
- `median()` - median value

- `mean()` - mean
- `sd()` - standard deviation
- `var()` - variance
- `max()` - maximum value
- `which.max()` - index of the first element with the maximum value
- `min()` - minimum value
- `which.min()` - index of the first element with the minimum value

Try these out using the vector `rain`. Note that R is case sensitive - `Mean()` is considered different from `mean()`, so if we type `Mean(rain)` R will tell us that it cannot find this function.

```
mean(rain)
#> [1] 0.8
min(rain)
#> [1] 0
which.min(rain)
#> Wednesday
#>       3
```

We may also be interested in the order of the values. The `sort()` function sorts the values of a vector, whereas the `order()` function returns the permutation of the elements to be in sorted order. The last line of code below sorts the days of the week from smallest to largest rain value.

```
rain
#>     Monday      Tuesday Wednesday Thursday      Friday
#>     5.0        0.1        0.0        0.0        0.5        0.0        0.0
order(rain)
#> [1] 3 4 6 7 2 5 1
days[order(rain)]
#> [1] "Wednesday" "Thursday"   "Saturday"   "Sunday"    "Tuesday"
#> [6] "Friday"     "Monday"
```

Both of these functions have an extra possible argument `decreasing`, which has a default value of FALSE. We can specify this to be TRUE to find the days of the week sorted from largest to smallest rainfall.

```
days[order(rain, decreasing=TRUE)]
#> [1] "Monday"     "Friday"      "Tuesday"     "Wednesday"   "Thursday"
#> [6] "Saturday"   "Sunday"
```

## 2.3 Factors

A **factor** is a special kind of vector that behaves exactly like a regular vector except that it represents values from a category. In particular, a factor keeps track of all possible values of that category, which are called the **levels** of the factor. Factors will be especially helpful when we start getting into data analysis and have categorical columns. The `as.factor()` function will convert a vector to a factor.

```
days <- c("Monday", "Tuesday", "Wednesday", "Monday", "Thursday", "Wednesday")
days_fct <- as.factor(days)

class(days_fct)
#> [1] "factor"
levels(days_fct)
#> [1] "Monday"      "Thursday"     "Tuesday"      "Wednesday"
```

Above, we did not specify the possible levels for our column. Instead, R found all values in the vector `days` and set these equal to the levels of the factor. Because of this, if we try to change one of the levels to 'Friday', we will get an error. Uncomment the line below to see the error message.

```
#days_fct[2] <- "Friday"
```

We can avoid this error by specifying the levels using the `factor()` function instead of the `as.factor()` function.

```
days <- c("Monday", "Tuesday", "Wednesday", "Monday", "Thursday", "Wednesday")
days_fct <- factor(days,
                    levels = c("Monday", "Tuesday", "Wednesday", "Thursday",
                               "Friday", "Saturday", "Sunday"))

class(days_fct)
#> [1] "factor"
levels(days_fct)
#> [1] "Monday"      "Tuesday"      "Wednesday"   "Thursday"    "Friday"
#> [6] "Saturday"    "Sunday"
days_fct[2] <- "Friday"
```

Factors can also be used for numeric vectors. For example, we might have a vector that is 0/1 that represents whether or not a day is a weekend. This can also only take on certain values (0 or 1).

```

weekend <- as.factor(c(1, 0, 0, 0, 1, 1))
levels(weekend)
#> [1] "0" "1"

```

## 2.4 Matrices

Matrices are similar to vectors in that they store data of the same type, but matrices are two-dimensional (as opposed to one-dimensional vectors), and consist of both rows and columns.

Below, we create a matrix reporting the daily rainfall over multiple weeks. We can create a matrix using the `matrix(data, nrow, ncol, byrow)` function. This creates a `nrow` by `ncol` matrix from the vector `data` values filling in by row if `byrow` is TRUE and by column otherwise. Run the code below. Then, change the last argument to `byrow=FALSE` and see what happens to the values.

```

rainfall <- matrix(c(5,6,0.1,3,0,1,0,1,0.4,0.2,0.5,0.3,0,0), ncol=7, nrow=2, byrow=TRUE)
rainfall
#>      [,1] [,2] [,3] [,4] [,5] [,6] [,7]
#> [1,]    5   6.0  0.1  3.0  0.0    1    0
#> [2,]    1   0.4  0.2  0.5  0.3    0    0

```

We can find the dimensions of a matrix using the `nrow()`, `ncol()`, or `dim()` functions, which return the number of rows, the number of columns, and both the number of rows and columns, respectively.

```

nrow(rainfall)
#> [1] 2
ncol(rainfall)
#> [1] 7
dim(rainfall)
#> [1] 2 7

```

### 2.4.1 Indexing a Matrix

Since matrices are two-dimensional, a single value is indexed by both its row number and its column number. This means that to access a subset of values in a matrix, we need to provide row and column indices. Below, we access a single value in the 1st row and the 4th column. The first value is always the row index and the second value is always the column index.

```
rainfall[1,4]
#> [1] 3
```

As before, we can also provide multiple indices to get multiple values. Below, we choose multiple columns but we can also choose multiple rows (or multiple rows and multiple columns!).

```
rainfall[1,c(4,5,7)]
#> [1] 3 0 0
```

As with vectors, we can also use booleans to index a matrix by providing boolean values for the rows and/or columns. Note that below we give a vector for the row indices and no values for the columns. Since we did not specify any column indices, this will select all of them.

```
rainfall[c(FALSE, TRUE), ]
#> [1] 1.0 0.4 0.2 0.5 0.3 0.0 0.0
```

Let's do the opposite and select some columns and all rows.

```
rainfall[,c(TRUE, TRUE, FALSE, FALSE, FALSE, FALSE, FALSE)]
#>      [,1] [,2]
#> [1,]     5   6.0
#> [2,]     1   0.4
```

As with vectors, we can specify row names and column names to access entries instead of using indices. The `colnames()` and `rownames()` functions allow us to specify the column and row names, respectively.

```
colnames(rainfall) <- c("Monday", "Tuesday", "Wednesday", "Thursday",
                         "Friday", "Saturday", "Sunday")
rownames(rainfall) <- c("Week1", "Week2")
rainfall["Week1",c("Friday","Saturday")]
#> Friday Saturday
#>       0           1
```

## 2.4.2 Editing a Matrix

If we want to change the values in a matrix, we need to first index those values and then assign them the new value(s). Below, we change a single entry to be 3 and then update several values to all be 0. Note that we do not provide multiple 0's on the right-hand side, as R will infer that all values should be set to 0.

```

rainfall["Week1", "Friday"] <- 3

rainfall["Week1", c("Monday", "Tuesday")] <- 0
print(rainfall)
#>           Monday Tuesday Wednesday Thursday Friday Saturday Sunday
#> Week1      0     0.0      0.1     3.0    3.0      1     0
#> Week2      1     0.4      0.2     0.5    0.3      0     0

```

Further, we can append values to our matrix by adding rows or columns through the `rbind()` and `cbind()` functions. The first function appends a row (or multiple rows) to a matrix and the second appends a column (or multiple columns). Note that below I provide a row and column name when passing in the additional data. If I hadn't specified these names, then those rows and columns would not be named.

```

rainfall <- rbind(rainfall, "Week3" = c(0.4, 0.0, 0.0, 0.0, 1.2, 2.2, 0.0))
rainfall <- cbind(rainfall, "Total" = c(7.1, 2.4, 3.8))
print(rainfall)
#>           Monday Tuesday Wednesday Thursday Friday Saturday Sunday Total
#> Week1      0.0     0.0      0.1     3.0    3.0      1.0     0   7.1
#> Week2      1.0     0.4      0.2     0.5    0.3      0.0     0   2.4
#> Week3      0.4     0.0      0.0     0.0    1.2      2.2     0   3.8

```

Here is an example where we bind two matrices by column. Note that whenever we bind two matrices together, we have to be sure that their dimensions are compatible and that they are of the same type.

```

A <- matrix(c(1,2,3,4), nrow=2)
B <- matrix(c(5,6,7,8), nrow=2)
C <- cbind(A, B)
C
#>      [,1] [,2] [,3] [,4]
#> [1,]    1    3    5    7
#> [2,]    2    4    6    8

```

As with vectors, most mathematical operators (+, -, \*, / etc.) are applied element-wise in R.

```

A+B
#>      [,1] [,2]
#> [1,]    6   10
#> [2,]    8   12

```

```
exp(C)
#>      [,1] [,2] [,3] [,4]
#> [1,] 2.72 20.1 148 1097
#> [2,] 7.39 54.6 403 2981
```

### 2.4.3 Practice Question

Create a 3x4 matrix of all 1's using the `rep()` and `matrix()` functions. Then select the first and third columns using indexing which will return a 3x2 matrix of all ones.

```
# Insert your solution here:
```

## 2.5 Data Frames

Matrices can store data like the rainfall data, where everything is of the same type. However, if we want to capture more complex data records, we also want to allow for different measurement types: this is where data frames come in. A data frame is like a matrix in that data frames are two-dimensional, but unlike matrices, data frames allow for each column to be a different type. In this case, each row corresponds to a single data entry (or observation) and each column corresponds to a different variable.

For example, suppose that, for every day in a study, we want to record the temperature, rainfall, and day of the week. Temperature and rainfall can be numeric values, but day of the week will be character type. We create a data frame using the `data.frame()` function. Note that I am providing column names for each vector (column).

The `head()` function prints the first six rows of a data frame (to avoid printing very large datasets). In our case, all the data is shown because we only created four rows. The column names are displayed as well as their type. By contrast, the `tail()` function prints the last six rows of a data frame.

```
weather_data <- data.frame(day_of_week = c("Monday", "Tuesday", "Wednesday", "Monday"),
                           temp = c(70, 62, 75, 50), rain = c(5, 0.1, 0.0, 0.5))
head(weather_data)
#>   day_of_week temp rain
#> 1     Monday    70  5.0
#> 2     Tuesday    62  0.1
#> 3   Wednesday    75  0.0
#> 4     Monday    50  0.5
```

The `dim()`, `nrow()`, and `ncol()` functions return the dimensions, number of rows, and number of columns of a data frame, respectively.

```
dim(weather_data)
#> [1] 4 3
nrow(weather_data)
#> [1] 4
ncol(weather_data)
#> [1] 3
```

The column names can be found (or assigned) using the `colnames()` or `names()` function. These were specified when I created the data. On the other hand, the row names are currently the indices.

```
colnames(weather_data)
#> [1] "day_of_week" "temp"           "rain"
rownames(weather_data)
#> [1] "1" "2" "3" "4"
names(weather_data)
#> [1] "day_of_week" "temp"           "rain"
```

We update the row names to be more informative as with a matrix using the `rownames()` function.

```
rownames(weather_data) <- c("6/1", "6/2", "6/3", "6/8")
head(weather_data)
#>   day_of_week temp rain
#> 6/1     Monday  70  5.0
#> 6/2    Tuesday  62  0.1
#> 6/3 Wednesday  75  0.0
#> 6/8     Monday  50  0.5
```

### 2.5.1 Indexing a Data Frame

We can select elements of the data frame using its indices in the same way as we did with matrices. Below, we access a single value and then a subset of our data frame. The subset returned is itself a data frame. Note that the second line below returns a data frame.

```
weather_data[1,2]
#> [1] 70
weather_data[1,c("day_of_week","temp")]
```

```
#>      day_of_week temp
#> 6/1      Monday    70
```

Another useful way to access the columns of a data frame is by using the `$` accessor and the column name.

```
weather_data$day_of_week
#> [1] "Monday"     "Tuesday"     "Wednesday"   "Monday"
weather_data$temp
#> [1] 70 62 75 50
```

The column `day_of_week` is a categorical column, but it can only take on a limited number of values. For this kind of column, it is often useful to convert that column to a factor as we did before.

```
weather_data$day_of_week <- factor(weather_data$day_of_week)
levels(weather_data$day_of_week)
#> [1] "Monday"     "Tuesday"     "Wednesday"
```

## 2.5.2 Editing a Data Frame

As with matrices, we can change values in a data frame by indexing those entries.

```
weather_data[1, "rain"] <- 2.2
weather_data
#>      day_of_week temp rain
#> 6/1      Monday    70  2.2
#> 6/2      Tuesday   62  0.1
#> 6/3      Wednesday 75  0.0
#> 6/8      Monday    50  0.5
```

The `rbind()` functions and `cbind()` functions also work for data frames in the same way as for matrices. However, another way to add a column is to directly use the `$` accessor. Below, we add a categorical column called `aq_warning`, indicating whether there was an air quality warning that day.

```
weather_data$aq_warning <- as.factor(c(1, 0, 0, 0))
weather_data
#>      day_of_week temp rain aq_warning
#> 6/1      Monday    70  2.2           1
```

```
#> 6/2      Tuesday   62  0.1      0
#> 6/3      Wednesday 75  0.0      0
#> 6/8      Monday    50  0.5      0
```

### 2.5.3 Practice Question

Add a column to `weather_data` called `air_quality_index` using the `rep()` function so that all values are `NA` (the missing value in R). Then, index the second value of this column and set the value to be `57`. The result should look like this:

```
# Insert your solution here:
```

## 2.6 Lists

A data frame is actually a special kind of another data structure called a **list**, which is a collection of objects under the same name. These objects can be vectors, matrices, data frames, or even other lists! There does not have to be any relation in size, type, or other attribute between different members of the list. Below, we create an example list using the `list()` function, which takes in a series of objects. What are the types of each element of the list? We can access each element using the index, but here we need to use double brackets.

```
ex_list <- list("John", c("ibuprofen", "metformin"), c(136, 142, 159))
print(ex_list)
#> [[1]]
#> [1] "John"
#>
#> [[2]]
#> [1] "ibuprofen" "metformin"
#>
#> [[3]]
#> [1] 136 142 159
ex_list[[2]]
#> [1] "ibuprofen" "metformin"
```

More often, however, it is useful to name the elements of the list for easier access. Let's create this list again but this time give names to each object.

```

ex_list <- list(name="John", medications = c("ibuprofen", "metformin"),
                 past_weights = c(136, 142, 159))
print(ex_list)
#> $name
#> [1] "John"
#>
#> $medications
#> [1] "ibuprofen" "metformin"
#>
#> $past_weights
#> [1] 136 142 159
ex_list$medications
#> [1] "ibuprofen" "metformin"

```

To edit a list, we can use indexing to access different objects in the list and then assign them to new values. Additionally, we can add objects to the list using the `$` accessor.

```

ex_list$supplements <- c("vitamin D", "biotin")
ex_list$supplements[2] <- "collagen"
ex_list
#> $name
#> [1] "John"
#>
#> $medications
#> [1] "ibuprofen" "metformin"
#>
#> $past_weights
#> [1] 136 142 159
#>
#> $supplements
#> [1] "vitamin D" "collagen"

```

## 2.7 Recap Video

<https://www.youtube.com/embed/YKCQ6uhg0fM>

## 2.8 Exercises

1. Recreate the following data frame in R, where `temperature` and `co2` represent the average temperature in Fahrenheit and the average CO<sub>2</sub> concentrations in mg/m<sup>3</sup> for the month of January 2008, and name it `city_air_quality`.
2. Create a character vector named `precipitation` with entries Yes or No indicating whether or not there was more precipitation than average in January 2008 in these cities (you can make this information up yourself). Then, append this vector to the `city_air_quality` data frame as a new column.
3. Convert the categorical column `precipitation` to a factor. Then, add the following row to the data frame `city_air_quality` using the `rbind()` function:
4. Use single square brackets to access the precipitation and CO<sub>2</sub> concentration entries for San Francisco and Paris in your data frame. Then, create a list `city_list` which contains two lists, one for San Francisco and one for Paris, where each inner list contains the city name, precipitation, and CO<sub>2</sub> concentration information for that city.

# 3 Working with Data Files in R

In this chapter, we will be working with data in R. To start, we need to load our data into R: this requires identifying the type of data file we have (e.g. .csv, .xlsx, .dta) and finding the appropriate function to load in the data. This will create a data frame object containing the information from the file. After demonstrating how to load in such data, this chapter will show you how to find information about data columns, including finding missing values, summarizing columns, and subsetting the data. Additionally, we look at how to create new columns through some simple transformations.

In this chapter and all future chapters, we will load in the required libraries at the start of the chapter - for example, in this particular chapter, we need a single library `HDSinRdata` that contains the sample data sets used in this book.

```
suppressPackageStartupMessages(library(HDSinRdata))
```

## 3.1 Importing and Exporting Data

The data we will use in this chapter contains information about patients who visited one of the University of Pittsburgh's seven pain management clinics. This includes patient-reported pain assessments using the Collaborative Health Outcomes Information Registry (CHOIR) at baseline and at a 3-month follow-up. You can use the help operator `?pain` to learn more about the source of this data and to read its column descriptions. Since this data is available in our R package, we can use the `data` function to load this data into our environment. Note that this data has 21,659 rows and 92 columns.

```
data(pain)
dim(pain)
#> [1] 21659     92
```

In general, the data you will be using will not be available in R packages and will instead exist in one or more data files on your personal computer. In order to load in this data to R, you need to use the function that corresponds to the file type you have. For example, you can load a .csv file using the `read.csv()` function in base R or using the `read_csv()` function from the `readr` package, both of which were shown in Chapter 1. As an example, we load

the `fake_names.csv` dataset below using both of these functions: looking at the print output below, we can see that there is slight difference in the data structure and data types storing the data between these two functions. The function `read.csv()` loads the data as a data frame, whereas the function `read_csv()` loads the data as a `spec_tbl_df`, a special type of data frame called a **tibble** that is used by the `tidyverse` packages. We will cover this data structure in more detail in Chapter 5. For now, note that you can use either function to read in a .csv file.

```
read.csv("data/fake_names.csv")
#>           Name  Age      DOB        City State
#> 1       Ken Irwin 37 6/28/85 Providence RI
#> 2 Delores Whittington 56 4/28/67 Smithfield RI
#> 3   Daniel Hughes 41 5/22/82 Providence RI
#> 4     Carlos Fain 83 2/2/40 Warren RI
#> 5    James Alford 67 2/23/56 East Providence RI
#> 6   Ruth Alvarez 34 9/22/88 Providence RI

readr::read_csv("data/fake_names.csv", show_col_types=FALSE)
#> # A tibble: 6 x 5
#>   Name          Age DOB     City   State
#>   <chr>        <dbl> <chr>   <chr>  <chr>
#> 1 Ken Irwin      37 6/28/85 Providence RI
#> 2 Delores Whittington 56 4/28/67 Smithfield RI
#> 3 Daniel Hughes    41 5/22/82 Providence RI
#> 4 Carlos Fain      83 2/2/40 Warren RI
#> 5 James Alford     67 2/23/56 East Providence RI
#> # i 1 more row
```

In addition to loading data into R, you may also want to save data from R into a data file you can access later or share with others. To write a data frame from R to a .csv file, you can use the `write.csv()` function. This function has three key arguments: the first argument is the data frame in R that you want to write to a file, the second argument is the file name or the full file path where you want to write the data, and the third argument is whether or not you want to include the row names as an extra column. In this case, we will not include row names. If you do not specify a file path, R will save the file in our current working directory.

```
df <- data.frame(x=c(1,0,1), y=c("A", "B", "C"))
write.csv(df, "data/test.csv", row.names=FALSE)
```

If your data is not in a .csv file, you may need to use another package to read in the file. The two most common packages are the `readxl` package, which makes it easy to read in Excel files,

and the `haven` package, which can import SAS, SPSS, and Stata files. For each function, you need to specify the file path to the data file.

- **Excel Files:** You can read in a .xls or .xlsx file using `readxl::read_excel()`, which allows you to specify a sheet and/or cell range within a file. (e.g. `read_excel('test.xlsx', sheet="Sheet1")`)
- **SAS:** `haven::read_sas()` reads in .sas7bdat or .sas7bcat files, `haven::read_xpt()` reads in SAS transport files
- **Stata:** `haven::read_dta()` reads in .dta files
- **SPSS:** `haven::read_spss()` reads in .spss files

## 3.2 Summarizing and Creating Data Columns

We will now look at the data we have loaded into the data frame called `pain`. We use the `head()` function to print the first six rows. However, note that we have so many columns that all not of the columns are displayed! For those that are displayed, we can see the data type for each column under the column name. For example, we can see that the column `PATIENT_NUM` is a numeric column of type `dbl`. Because patients identification numbers are technically nominal in nature, we might consider whether we should make convert this column to a factor or a character representation later on. We can use the `names()` function to print all the column names. Note that columns `X101` to `X238` correspond to numbers on a body pain map (see the data documentation for the image of this map). Each of these columns has a 1 if the patient indicated that they have pain in that corresponding body part and a 0 otherwise.

```
head(pain)
#> # A tibble: 6 x 92
#>   PATIENT_NUM X101  X102  X103  X104  X105  X106  X107  X108  X109
#>   <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
#> 1     13118     0     0     0     0     0     0     0     0     0
#> 2     21384     0     0     0     0     0     0     0     0     0
#> 3      6240     0     0     0     0     0     0     0     0     0
#> 4      1827     0     0     0     0     0     0     0     0     0
#> 5     11309     0     0     0     0     0     0     0     0     0
#> # i 1 more row
#> # i 82 more variables: X110 <dbl>, X111 <dbl>, X112 <dbl>, X113 <dbl>,
#> #   X114 <dbl>, X115 <dbl>, X116 <dbl>, X117 <dbl>, X118 <dbl>,
#> #   X119 <dbl>, X120 <dbl>, X121 <dbl>, X122 <dbl>, X123 <dbl>,
#> #   X124 <dbl>, X125 <dbl>, X126 <dbl>, X127 <dbl>, X128 <dbl>,
#> #   X129 <dbl>, X130 <dbl>, X131 <dbl>, X132 <dbl>, X133 <dbl>,
```

```
#> #   X134 <dbl>, X135 <dbl>, X136 <dbl>, X201 <dbl>, X202 <dbl>, ...
names(pain)
#> [1] "PATIENT_NUM"
#> [2] "X101"
#> [3] "X102"
#> [4] "X103"
#> [5] "X104"
#> [6] "X105"
#> [7] "X106"
#> [8] "X107"
#> [9] "X108"
#> [10] "X109"
#> [11] "X110"
#> [12] "X111"
#> [13] "X112"
#> [14] "X113"
#> [15] "X114"
#> [16] "X115"
#> [17] "X116"
#> [18] "X117"
#> [19] "X118"
#> [20] "X119"
#> [21] "X120"
#> [22] "X121"
#> [23] "X122"
#> [24] "X123"
#> [25] "X124"
#> [26] "X125"
#> [27] "X126"
#> [28] "X127"
#> [29] "X128"
#> [30] "X129"
#> [31] "X130"
#> [32] "X131"
#> [33] "X132"
#> [34] "X133"
#> [35] "X134"
#> [36] "X135"
#> [37] "X136"
#> [38] "X201"
#> [39] "X202"
```

```
#> [40] "X203"
#> [41] "X204"
#> [42] "X205"
#> [43] "X206"
#> [44] "X207"
#> [45] "X208"
#> [46] "X209"
#> [47] "X210"
#> [48] "X211"
#> [49] "X212"
#> [50] "X213"
#> [51] "X214"
#> [52] "X215"
#> [53] "X216"
#> [54] "X217"
#> [55] "X218"
#> [56] "X219"
#> [57] "X220"
#> [58] "X221"
#> [59] "X222"
#> [60] "X223"
#> [61] "X224"
#> [62] "X225"
#> [63] "X226"
#> [64] "X227"
#> [65] "X228"
#> [66] "X229"
#> [67] "X230"
#> [68] "X231"
#> [69] "X232"
#> [70] "X233"
#> [71] "X234"
#> [72] "X235"
#> [73] "X236"
#> [74] "X237"
#> [75] "X238"
#> [76] "PAIN_INTENSITY_AVERAGE"
#> [77] "PROMIS_PHYSICAL_FUNCTION"
#> [78] "PROMIS_PAIN_BEHAVIOR"
#> [79] "PROMIS_DEPRESSION"
#> [80] "PROMIS_ANXIETY"
```

```
#> [81] "PROMIS_SLEEP_DISTURB_V1_0"
#> [82] "PROMIS_PAIN_INTERFERENCE"
#> [83] "GH_MENTAL_SCORE"
#> [84] "GH_PHYSICAL_SCORE"
#> [85] "AGE_AT_CONTACT"
#> [86] "BMI"
#> [87] "CCI_TOTAL_SCORE"
#> [88] "PAIN_INTENSITY_AVERAGE.FOLLOW_UP"
#> [89] "PAT_SEX"
#> [90] "PAT_RACE"
#> [91] "CCI_BIN"
#> [92] "MEDICAID_BIN"
```

Recall that the `$` operator can be used to access a single column. Alternatively, we can use double brackets `[]` to select a column. Below, we demonstrate both ways to print the first five values in the column with the patient's average pain intensity.

```
pain$PAIN_INTENSITY_AVERAGE[1:5]
#> [1] 7 5 4 7 8
pain[["PAIN_INTENSITY_AVERAGE"]][1:5]
#> [1] 7 5 4 7 8
```

### 3.2.1 Column Summaries

To explore the range and distribution of a column's values, we can use some of the base R functions. For example, the `summary()` function is a useful way to summarize a numeric column's values. Below, we can see that the pain intensity values range from 0 to 10 with a median value of 7 and that there is 1 NA value.

```
summary(pain$PAIN_INTENSITY_AVERAGE)
#>      Min. 1st Qu. Median     Mean 3rd Qu.    Max.    NA's
#> 0.00    5.00   7.00   6.49    8.00  10.00       1
```

We have already seen the `max()`, `min()`, `mean()`, and `median()` functions that could have computed some of these values for us separately. Since we do have an NA value, we add the `na.rm=TRUE` argument to these functions. Without this argument, the returned value for all of the functions will be NA.

```
min(pain$PAIN_INTENSITY_AVERAGE, na.rm=TRUE)
#> [1] 0
```

```
max(pain$PAIN_INTENSITY_AVERAGE, na.rm=TRUE)
#> [1] 10
mean(pain$PAIN_INTENSITY_AVERAGE, na.rm=TRUE)
#> [1] 6.49
median(pain$PAIN_INTENSITY_AVERAGE, na.rm=TRUE)
#> [1] 7
```

Additionally, the functions below are helpful for summarizing quantitative columns.

- `range()` - returns the minimum and maximum values for a numeric vector `x`
- `quantile()` - returns the sample quantiles for a numeric vector
- `IQR()` - returns the interquartile range for a numeric vector

By default, the `quantile()` function returns the sample quantiles.

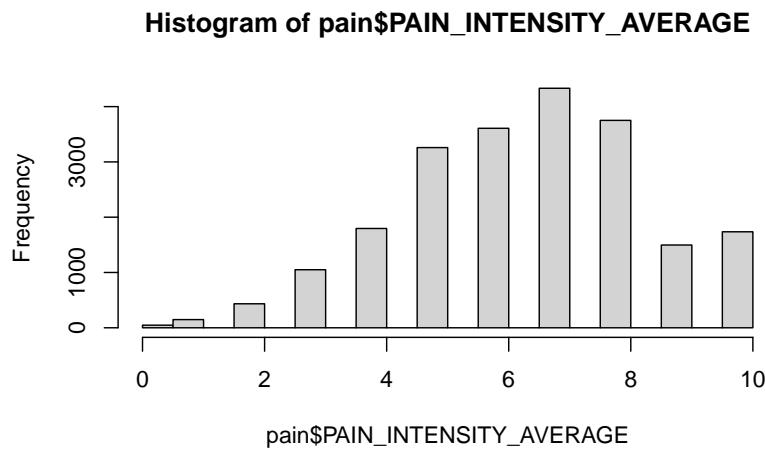
```
quantile(pain$PAIN_INTENSITY_AVERAGE, na.rm = TRUE)
#>  0%   25%   50%   75% 100%
#>  0     5     7     8    10
```

However, we can pass in a list of probabilities to use instead. For example, below we find the 0.1 and 0.9 quantiles. Again, we add the `na.rm=TRUE` argument.

```
quantile(pain$PAIN_INTENSITY_AVERAGE, probs = c(0.1, 0.9), na.rm=TRUE)
#> 10% 90%
#>  4    9
```

We can also plot a histogram of the sample distribution using the `hist()` function. We will look more in depth at how to change aspects of this histogram in Chapter 4.

```
hist(pain$PAIN_INTENSITY_AVERAGE)
```



### 3.2.2 Practice Question

Summarize the PROMIS\_SLEEP\_DISTURB\_V1\_0 column both numerically and visually. Your results should look like this:

```
# Insert your solution here:
```

We can also use the `summary()` function for categorical variables. In this case, R will find the counts for each level.

```
summary(pain$PAT_SEX)
#>      Length     Class    Mode
#>      21659 character character
```

For categorical columns, it is also useful to use the `table()` function, which returns the counts for each possible value, instead of the `summary()` function. By default, `table()` ignores NA values. However, we can set `useNA="always"` if we also want to display the number of NA values in the table output. Additionally, we can use the `prop.table()` function to convert the counts to proportions. Below, we can see that the column PAT\_SEX column, which corresponds to the reported patient sex, has a single missing value, and we can also see that around 60% of patients are female.

```
table(pain$PAT_SEX, useNA="always")
#>
#> female   male   <NA>
#> 13102   8556      1
```

```
prop.table(table(pain$PAT_SEX))
#>
#> female    male
#> 0.605   0.395
```

Note that this column is not actually a factor column yet, which we can check using the `is.factor()` function. We can convert it to one using `as.factor()`.

```
is.factor(pain$PAT_SEX)
#> [1] FALSE

pain$PAT_SEX <- as.factor(pain$PAT_SEX)
is.factor(pain$PAT_SEX)
#> [1] TRUE
```

### 3.2.3 Other Summary Functions

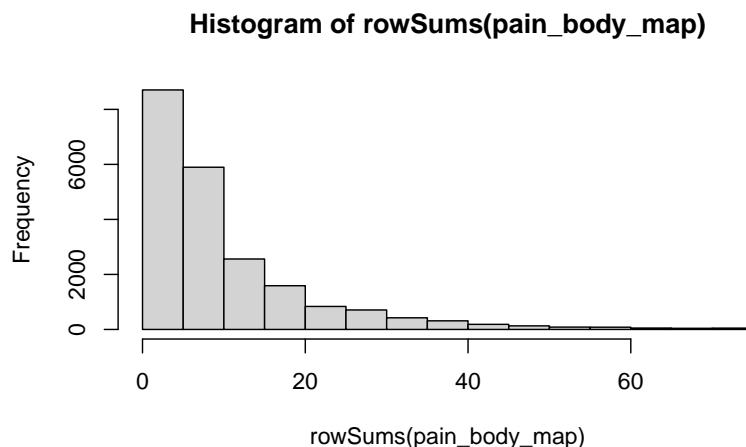
Sometimes we want to summarize information across multiple columns or rows. We can use the `rowSums()` and `colSums()` functions to sum over the rows or columns of a matrix or data frame. We first subset the data to the body pain map regions. In the first line of code, I select the column names pertaining to these columns. This allows me to select those columns in the second line of code and store this subset of the data as a new data frame called `pain_body_map`.

```
body_map_cols <- names(pain)[2:75]
pain_body_map <- pain[, body_map_cols]
head(pain_body_map)
#> # A tibble: 6 x 74
#>   X101  X102  X103  X104  X105  X106  X107  X108  X109  X110  X111
#>   <dbl> <dbl>
#> 1     0     0     0     0     0     0     0     0     0     0     0
#> 2     0     0     0     0     0     0     0     0     0     0     0
#> 3     0     0     0     0     0     0     0     0     0     0     0
#> 4     0     0     0     0     0     0     0     0     0     0     0
#> 5     0     0     0     0     0     0     0     0     0     0     0
#> # i 1 more row
#> # i 63 more variables: X112 <dbl>, X113 <dbl>, X114 <dbl>, X115 <dbl>,
#> #   X116 <dbl>, X117 <dbl>, X118 <dbl>, X119 <dbl>, X120 <dbl>,
#> #   X121 <dbl>, X122 <dbl>, X123 <dbl>, X124 <dbl>, X125 <dbl>,
#> #   X126 <dbl>, X127 <dbl>, X128 <dbl>, X129 <dbl>, X130 <dbl>,
```

```
#> #   X131 <dbl>, X132 <dbl>, X133 <dbl>, X134 <dbl>, X135 <dbl>,
#> #   X136 <dbl>, X201 <dbl>, X202 <dbl>, X203 <dbl>, X204 <dbl>, ...
```

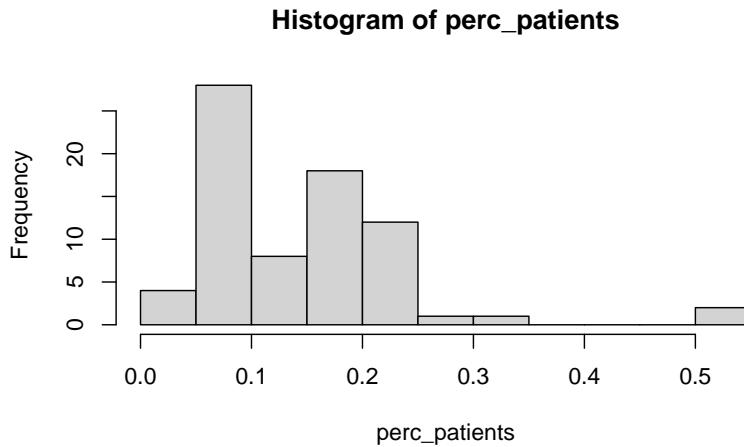
I now compute the row sums and column sums on this subset of data. The row sum for each patient is the total number of body parts in which they experience pain, whereas the column sum for each pain region is the total number of patients who experience pain in that area. The histogram below shows that most people select a low number of total regions.

```
hist(rowSums(pain_body_map))
```



We can also see that some body parts are more often selected than others. We create a vector called `perc_patients` below by finding the number of patients who selected each region divided by the total number of patients. The histogram shows that some body regions are selected by over 50% of patients!

```
perc_patients <- colSums(pain_body_map, na.rm=TRUE)/nrow(pain_body_map)
hist(perc_patients)
```



We use the `which.max()` function to see that the 55th region X219 is selected the most number of times. This corresponds to lower back pain.

```
which.max(perc_patients)
#> X219
#> 55
```

Another pair of useful functions are `pmin()` and `pmax()`. These functions take at least two vectors and find the pairwise minimum or maximum across those vectors, as shown below. For example, suppose you had two vectors,

```
v1 = c(5, 9, 12)
v2 = c(2, 18, 4)
pmax(v1, v2)
#> [1] 5 18 12
```

Looking back at the `pain` data, if we want to create a new column `lower_back_pain` that corresponds to whether someone selects *either* X218 or X219 we can use the `pmax()` function to find the maximum value between columns X218 and X219. We can see that almost 60% of patients select at least one of these regions.

```
lower_back <- pmax(pain_body_map$X218, pain_body_map$X219)
prop.table(table(lower_back))
#> lower_back
#>     0      1
#> 0.405 0.595
```

We might want to store the total number of pain regions and our indicator of whether or not a patient has lower back pain as new columns. We use our code above to create new columns in the pain data using the `$` operator. To be consistent with the column naming in the data, we use all upper case for our column names. The `dim()` function shows that our data has grown by two columns, as expected.

```
pain$NUM_REGIONS <- rowSums(pain_body_map)
pain$LOWER_BACK <- lower_back
dim(pain)
#> [1] 21659     94
```

Another useful function that allows us to perform computations over the rows or columns of a matrix or data frame is the `apply(X, MARGIN, FUN)` function, which takes in three arguments. The first argument is a data frame or matrix `X`, the second argument `MARGIN` indicates whether to compute over the rows (1) or columns (2), and the last argument is the function `FUN` to apply across that margin. The first example below finds the maximum value for each row in the data frame `pain_body_map`. Taking the minimum value of the row maximum values shows that every patient selected at least one body map region. In the second example, we find the sum of the body pain regions over the columns, which is equivalent to the example using `colSums()` above. In this case, we added the `na.rm=TRUE` argument. The `apply()` function will pass additional arguments to the function `FUN`.

```
any_selected <- apply(pain_body_map, 1, max)
min(any_selected, na.rm=TRUE)
#> [1] 1

perc_patients <- apply(pain_body_map, 2, sum, na.rm=TRUE)/nrow(pain_body_map)
summary(perc_patients)
#>   Min. 1st Qu. Median   Mean 3rd Qu.   Max.
#> 0.032  0.070  0.136  0.144  0.181  0.542
```

### 3.2.4 Practice Question

Find the sum of each of the PROMIS measures across all patients using `apply()` and then using `colSums()`. Verify that these two methods return the same result, which is given below:

```
# Insert your solution here:
```

### 3.2.5 Missing, Infinite, and NaN Values

As we saw above, this data contains some missing values, which are represented as `NA` in R. R treats these values as if they were unknown, which is why we have to add the `na.rm=TRUE` argument to functions like `sum()` and `max()`. In the example below, we can see that R figures out that 1 plus an unknown number is also unknown!

```
NA+1  
#> [1] NA
```

We can determine whether a value is missing using the function `is.na()`. This function returns `TRUE` if the value is `NA` and `FALSE` otherwise. We can then sum up these values for a single column, since each `TRUE` value corresponds to a value of 1 and each `FALSE` corresponds to a value of 0. Below we can see that there is a single `NA` value for the column `PATIENT_NUM`, which is the patient ID number.

```
sum(is.na(pain$PATIENT_NUM))  
#> [1] 1
```

If we want to calculate the sum of `NA` values for each column instead of just a single column, we can use the `apply` function. Since we want to apply this computation over the columns, the second argument has value 2. Recall that the last argument is the function we want to call for each column. In this case, we want to apply the combination of the `sum()` and `is.na()` function. To do so, we have to specify this function ourselves. This is called an **anonymous function** since it doesn't have a name.

```
num_missing_col <- apply(pain, 2, function(x) sum(is.na(x)))  
min(num_missing_col)  
#> [1] 1
```

Interestingly, we can see that there is at least one missing value in each column. It might be the case that there is a row with all `NA` values. Let's apply the same function by row. Taking the maximum, we can see that row 11749 has all `NA` values.

```
num_missing_row <- apply(pain, 1, function(x) sum(is.na(x)))  
max(num_missing_row)  
#> [1] 94  
which.max(num_missing_row)  
#> [1] 11749
```

We remove that row and then find the percentage of missing values by column. We can see that the column with the highest percentage of missing values is the pain intensity at follow-up. In fact, only 33% of patients have a recorded follow-up visit.

```

pain <- pain[-11749,]
num_missing_col <- apply(pain, 2, function(x) sum(is.na(x))/nrow(pain))
num_missing_col
#>          PATIENT_NUM           X101
#>          0.00000           0.00000
#>          X102           X103
#>          0.00000           0.00000
#>          X104           X105
#>          0.00000           0.00000
#>          X106           X107
#>          0.00000           0.00000
#>          X108           X109
#>          0.00000           0.00000
#>          X110           X111
#>          0.00000           0.00000
#>          X112           X113
#>          0.00000           0.00000
#>          X114           X115
#>          0.00000           0.00000
#>          X116           X117
#>          0.00000           0.00000
#>          X118           X119
#>          0.00000           0.00000
#>          X120           X121
#>          0.00000           0.00000
#>          X122           X123
#>          0.00000           0.00000
#>          X124           X125
#>          0.00000           0.00000
#>          X126           X127
#>          0.00000           0.00000
#>          X128           X129
#>          0.00000           0.00000
#>          X130           X131
#>          0.00000           0.00000
#>          X132           X133
#>          0.00000           0.00000
#>          X134           X135

```

#>	0.00000	0.00000
#>	X136	X201
#>	0.00000	0.00000
#>	X202	X203
#>	0.00000	0.00000
#>	X204	X205
#>	0.00000	0.00000
#>	X206	X207
#>	0.00000	0.00000
#>	X208	X209
#>	0.00000	0.00000
#>	X210	X211
#>	0.00000	0.00000
#>	X212	X213
#>	0.00000	0.00000
#>	X214	X215
#>	0.00000	0.00000
#>	X216	X217
#>	0.00000	0.00000
#>	X218	X219
#>	0.00000	0.00000
#>	X220	X221
#>	0.00000	0.00000
#>	X222	X223
#>	0.00000	0.00000
#>	X224	X225
#>	0.00000	0.00000
#>	X226	X227
#>	0.00000	0.00000
#>	X228	X229
#>	0.00000	0.00000
#>	X230	X231
#>	0.00000	0.00000
#>	X232	X233
#>	0.00000	0.00000
#>	X234	X235
#>	0.00000	0.00000
#>	X236	X237
#>	0.00000	0.00000
#>	X238	PAIN_INTENSITY_AVERAGE
#>	0.00000	0.00000

```

#>          PROMIS_PHYSICAL_FUNCTION          PROMIS_PAIN_BEHAVIOR
#>          0.00000                          0.29412
#>          PROMIS_DEPRESSION                PROMIS_ANXIETY
#>          0.00402                          0.00402
#>          PROMIS_SLEEP_DISTURB_V1_0        PROMIS_PAIN_INTERFERENCE
#>          0.00402                          0.00697
#>          GH_MENTAL_SCORE                GH_PHYSICAL_SCORE
#>          0.13602                          0.13602
#>          AGE_AT_CONTACT                  BMI
#>          0.00000                          0.26004
#>          CCI_TOTAL_SCORE   PAIN_INTENSITY_AVERAGE.FOLLOW_UP
#>          0.00000                          0.67042
#>          PAT_SEX                         PAT_RACE
#>          0.00000                          0.00651
#>          CCI_BIN                         MEDICAID_BIN
#>          0.00000                          0.01385
#>          NUM_REGIONS                     LOWER_BACK
#>          0.00000                          0.00000

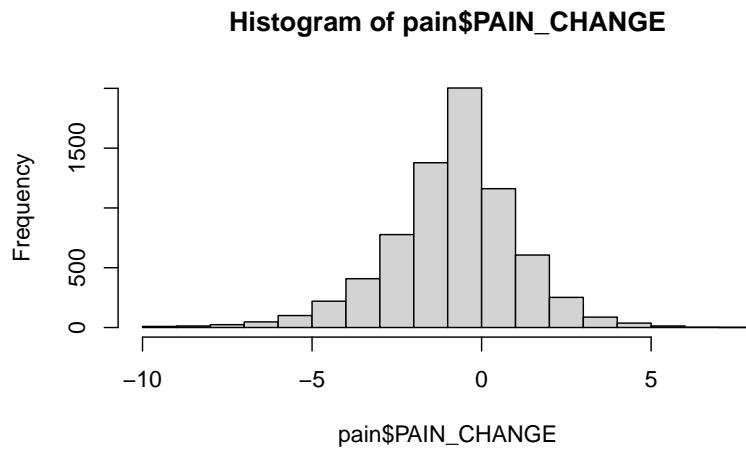
```

We will create two new columns: first, we create a column for the change in pain at follow-up, and second, we create a column which is the percent change in pain at follow-up.

```

pain$PAIN_CHANGE <- pain$PAIN_INTENSITY_AVERAGE.FOLLOW_UP - pain$PAIN_INTENSITY_AVERAGE
hist(pain$PAIN_CHANGE)

```



```

pain$PERC_PAIN_CHANGE <- pain$PAIN_CHANGE/pain$PAIN_INTENSITY_AVERAGE
summary(pain$PERC_PAIN_CHANGE)
#>   Min. 1st Qu. Median   Mean 3rd Qu.   Max.   NA's
#>    -1       0       0      Inf       0      Inf    14520

```

In the summary of the percent change, we can see that the maximum value is `Inf`. This is R's representation of infinity. This occurred because some patients have an initial pain score of 0, which creates infinite values when we divide through by this value to find the percent change. We can test whether something is infinite using the `is.infinite()` or `is.finite()` functions. This shows that there were three patients with infinite values. The value `-Inf` is used to represent negative infinity.

```

sum(is.infinite(pain$PERC_PAIN_CHANGE))
#> [1] 3

```

Another special value in R is `NaN`, which stands for “Not a Number”. For example,  $0/0$  will result in a `NaN` value. We can test for `NaN` values using the `is.nan()` function.

```

0/0
#> [1] NaN

```

Looking back at the missing values, there are two useful functions for selecting the complete cases in a data frame. The `na.omit()` function returns the data frame with incomplete cases removed, whereas `complete.cases()` returns TRUE/FALSE values for each row indicating whether each row is complete, which we can then use to select the rows with TRUE values. Below, we see both approaches select the same number of rows.

```

pain_sub1 <- na.omit(pain)
pain_sub2 <- pain[complete.cases(pain),]
dim(pain_sub1)
#> [1] 2413   96
dim(pain_sub2)
#> [1] 2413   96

```

### 3.3 Using Logic to Subset, Summarize, and Transform

Above, we used TRUE/FALSE values to select rows in a data frame. The logic operators in R allow us to expand on this capability to write more complex logic. The operators are given below.

- `<` less than
- `<=` less than or equal to
- `>` greater than
- `>=` greater than or equal to
- `==` equal to
- `!=` not equal to
- `a %in% b` a's value is in a vector of values b

The first six operators are a direct comparison between two values and are demonstrated below.

```
2 < 2
#> [1] FALSE
2 <= 2
#> [1] TRUE
3 > 2
#> [1] TRUE
3 >= 2
#> [1] TRUE
"A" == "B"
#> [1] FALSE
"A" != "B"
#> [1] TRUE
```

The operators assume there is a natural ordering or comparison between values. For example, for strings the ordering is alphabetical and for logical operators we use their numeric interpretation (TRUE = 1, FALSE = 0).

```
"A" < "B"
#> [1] TRUE
TRUE < FALSE
#> [1] FALSE
```

The `%in%` operator is slightly different. This operator checks whether a value is in a set of possible values. Below, we can check whether values are in the set `c(4,1,2)`.

```
1 %in% c(4,1,2)
#> [1] TRUE
c(0,1,5) %in% c(4,1,2)
#> [1] FALSE TRUE FALSE
```

Additionally, we can use the following operators, which allow us to negate or combine logical operators.

- `!x` - the **NOT** operator `!` reverses TRUE/FALSE values
- `x | y` - the **OR** operator `|` checks whether *either* `x` or `y` is equal to TRUE
- `x & y` - the **AND** operator `&` checks whether *both* `x` and `y` are equal to TRUE
- `xor(x,y)` - the **xor** function checks whether exactly one of `x` or `y` is equal to TRUE (called exclusive or)
- `any(x)` - the **any** function checks whether any value in `x` is TRUE (equivalent to using an OR operator `|` between all values)
- `all(x)` - the **all** function checks whether all values in `x` are TRUE (equivalent to using an AND operator `&` between all values)

Some simple examples for each are given below.

```
!(2 < 3)
#> [1] FALSE
("Alice" < "Bob") | ("Alice" < "Aaron")
#> [1] TRUE
("Alice" < "Bob") & ("Alice" < "Aaron")
#> [1] FALSE
xor(TRUE, FALSE)
#> [1] TRUE
any(c(FALSE, TRUE, TRUE))
#> [1] TRUE
all(c(FALSE, TRUE, TRUE))
#> [1] FALSE
```

Let's demonstrate these operators on the pain data. We first update the Medicaid column by making the character values more informative. The logic on the left hand side selects those that do or do not have Medicaid and then assigns those values to the new ones.

```
pain$MEDICAID_BIN[pain$MEDICAID_BIN == "no"] <- "No Medicaid"
pain$MEDICAID_BIN[pain$MEDICAID_BIN == "yes"] <- "Medicaid"
table(pain$MEDICAID_BIN)
#>
#>     Medicaid No Medicaid
#>         4601      16757
```

Additionally, we could subset the data to only those who have follow-up. The not operator `!` will reverse the TRUE/FALSE values returned from the `is.na()` function. Therefore, the new value will be TRUE if the follow-up value is *not* NA.

```
pain_follow_up <- pain[!is.na(pain$PAIN_INTENSITY_AVERAGE.FOLLOW_UP),]
```

Earlier, we created a column indicating whether or not a patient has lower back pain. We now use the `any()` function to check whether a patient has general back pain. If at least one of these values is equal to 1, then the function will return TRUE. If we had used the `all()` function instead, this would check whether all values are equal to 1, indicating that a patient has pain on their whole back.

```
pain$BACK <- any(pain$X208==1, pain$X209==1, pain$X212==1, pain$X213==1,  
                  pain$X218==1, pain$X219==1)
```

### 3.3.1 Practice Question

Subset the `pain` data to those who have follow-up and have an initial average pain intensity of 5 or above. Name this subset of the data `pain_subset`. Print the head of this data. The first 6 patient IDs in this new dataset should be 13118, 21384, 1827, 11309, 11093, and 14667.

```
# Insert your solution here:
```

Lastly, we look at the column for patient race `PAT_RACE`. The `table()` function shows that most patients are `WHITE` or `BLACK`. Given how few observations are in the other categories, we may want to combine some of these levels into one.

```
table(pain$PAT_RACE)  
#> ALASKA NATIVE          AMERICAN INDIAN          BLACK  
#>                 2                  58                3229  
#> CHINESE               DECLINED             FILIPINO  
#>                 21                 121                  6  
#> GUAM/CHAMORRO         HAWAIIAN            INDIAN (ASIAN)  
#>                 1                  1                   49  
#> JAPANESE              KOREAN              NOT SPECIFIED  
#>                 9                  10                  4  
#> OTHER                  OTHER ASIAN OTHER PACIFIC ISLANDER  
#>                 1                  47                  12  
#> VIETNAMESE             WHITE  
#>                 6                 17940
```

Another way we could have found all possible values for this column is to use the `unique()` function. This function takes in a data frame or vector `x` and returns `x` with all duplicate rows or values removed.

```

unique(pain$PAT_RACE)
#> [1] "WHITE"                 "BLACK"
#> [3] "DECLINED"              "AMERICAN INDIAN"
#> [5] "INDIAN (ASIAN)"        "ALASKA NATIVE"
#> [7] NA                      "FILIPINO"
#> [9] "JAPANESE"              "VIETNAMESE"
#> [11] "KOREAN"                "CHINESE"
#> [13] "OTHER ASIAN"          "NOT SPECIFIED"
#> [15] "HAWAIIAN"              "OTHER PACIFIC ISLANDER"
#> [17] "OTHER"                  "GUAM/CHAMORRO"

```

To combine some of these levels, we can use the `%in%` operator. We first create an Asian, Asian American, or Pacific Islander race category and then create an American Indian or Alaska Native category.

```

aapi_values <- c("CHINESE", "HAWAIIAN", "INDIAN (ASIAN)", "FILIPINO", "VIETNAMESE",
                 "JAPANESE", "KOREAN", "GUAM/CHAMORRO", "OTHER ASIAN",
                 "OTHER PACIFIC ISLANDER")
pain$PAT_RACE[pain$PAT_RACE %in% aapi_values] <- "AAPI"
pain$PAT_RACE[pain$PAT_RACE %in% c("ALASKA NATIVE", "AMERICAN INDIAN")] <- "AI/AN"
table(pain$PAT_RACE)
#>
#>      AAPI      AI/AN      BLACK    DECLINED NOT SPECIFIED
#>      162       60      3229        121            4
#>      OTHER     WHITE
#>      1        17940

```

### 3.3.2 Other Selection Functions

Above, we selected rows using TRUE/FALSE boolean values. Instead, we could have also used the `which()` function. This function takes TRUE/FALSE values and returns the index values for all the TRUE values. We use this to treat those with race given as DECLINED as not specified.

```

pain$PAT_RACE[which(pain$PAT_RACE == "DECLINED")] <- "NOT SPECIFIED"

```

Another selection function is the `subset()` function. This function takes in two arguments. The first is the vector, matrix, or data frame to select from and the second is a vector of TRUE/FALSE values to use for row selection. We use this to find the observation with race marked as OTHER. We then update this race to also be marked as not specified.

```

subset(pain, pain$PAT_RACE == "OTHER")
#> # A tibble: 1 x 97
#>   PATIENT_NUM X101  X102  X103  X104  X105  X106  X107  X108  X109
#>   <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
#> 1      3588     1     1     1     0     1     1     1     0     0
#> # i 87 more variables: X110 <dbl>, X111 <dbl>, X112 <dbl>, X113 <dbl>,
#> #   X114 <dbl>, X115 <dbl>, X116 <dbl>, X117 <dbl>, X118 <dbl>,
#> #   X119 <dbl>, X120 <dbl>, X121 <dbl>, X122 <dbl>, X123 <dbl>,
#> #   X124 <dbl>, X125 <dbl>, X126 <dbl>, X127 <dbl>, X128 <dbl>,
#> #   X129 <dbl>, X130 <dbl>, X131 <dbl>, X132 <dbl>, X133 <dbl>,
#> #   X134 <dbl>, X135 <dbl>, X136 <dbl>, X201 <dbl>, X202 <dbl>,
#> #   X203 <dbl>, X204 <dbl>, X205 <dbl>, X206 <dbl>, X207 <dbl>, ...

pain$PAT_RACE[pain$PATIENT_NUM==3588] <- "NOT SPECIFIED"
table(pain$PAT_RACE)
#>
#>          AAPI        AI/AN      BLACK NOT SPECIFIED       WHITE
#>          162             60           3229            126         17940

```

## 3.4 Recap Video

In the video below, we reference the population mean and standard deviations for the instrument variables in the data. Use the help operator (`?pain`) to refresh your memory about these variables.

<https://www.youtube.com/embed/EU0UJN68OWQ>

## 3.5 Exercises

For these exercises, we will again be using the `pain` data from the `HDSinRdata` package.

1. Print summary statistics for the `PROMIS_PHYSICAL_FUNTION` and `PROMIS_ANXIETY` columns in this dataset. Read the data documentation for these two columns, which both have range 0 to 100, and then comment on the distributions of these columns.
2. Create frequency tables for the values of `PAT_SEX` and `PAT_RACE` and summarize what these tables tell you about the distributions of these demographic characteristics.

3. Create a new data frame called `pain.new` that doesn't contain patients with NA values for both `GH_MENTAL_SCORE` and `GH_PHYSICAL_SCORE`, which are the PROMIS global mental and physical scores, respectively.
4. Create a vector of the proportion of patients who reported pain in each of the pain regions. Then, find the minimum, median, mean, maximum, standard deviation, and variance of this vector.
5. Calculate the median and interquartile range of the distribution of the total number of painful leg regions selected for each patient. Then, write a few sentences explaining anything interesting you observe about this distribution in the context of this dataset.
6. Look at the distribution of average pain intensity between patients with only one pain region selected vs. those with more than one region selected. What do you notice?
7. Create a histogram to plot the distribution of the `PAIN_INTENSITY_AVERAGE.FOLLOW_UP` column. Then, create a table summarizing how many patients had missing values in this column. Finally, choose two columns to compare the distribution between those with and without missing follow up. What do you notice?

## **Part II**

# **Exploratory Analysis**

# 4 Intro to Exploratory Data Analysis

In the last chapter, we learned about loading data into R and practiced selecting and summarizing columns and rows of the data. In this chapter, we will learn how to conduct more exploratory analysis, focusing on the univariate and bivariate sample distributions of the data. The first half focuses on using base R to create basic plots and summaries. In the second half, we show how to create summary plots using the `GGally` package and tables using the `gt` and `gtsummary` packages.

```
suppressPackageStartupMessages(library(HDSinRdata))
suppressPackageStartupMessages(library(GGally))
suppressPackageStartupMessages(library(gt))
suppressPackageStartupMessages(library(gtsummary))
```

## 4.1 Univariate Distributions

In this chapter, we will use a sample of the National Health and Nutrition Examination Survey ([NHANES](#)) containing lead, blood pressure, BMI, smoking status, alcohol use, and demographic variables from NHANES 1999-2018. There are 31,625 observations in this sample. Use the help operator `?NHANESSsample` to read the column descriptions.

```
data(NHANESSsample)
dim(NHANESSsample)
#> [1] 31265     21
names(NHANESSsample)
#>  [1] "ID"          "AGE"         "SEX"        "RACE"
#>  [5] "EDUCATION"   "INCOME"      "SMOKE"      "YEAR"
#>  [9] "LEAD"        "BMI_CAT"    "LEAD_QUANTILE" "HYP"
#> [13] "ALC"         "DBP1"       "DBP2"       "DBP3"
#> [17] "DBP4"       "SBP1"       "SBP2"       "SBP3"
#> [21] "SBP4"
```

To start our exploration, we will look at whether there are any missing values. We use the `complete.cases()` function to observe that there are no complete cases. We also see that

the subsequent blood pressure measurements and alcohol use have the highest percentage of missing values. For demonstration, we choose to only keep the first systolic and diastolic blood pressure measurements and do a complete case analysis using the `na.omit()` function to define our complete data frame `nhanes_df`.

```
sum(complete.cases(NHANESsample))
#> [1] 0
apply(NHANESsample, 2, function(x) sum(is.na(x))/nrow(NHANESsample))
#>          ID           AGE           SEX           RACE      EDUCATION
#> 0.0000000 0.0000000 0.0000000 0.0000000 0.000672
#> INCOME       SMOKE        YEAR         LEAD    BMI_CAT
#> 0.0000000 0.0000000 0.0000000 0.0000000 0.000000
#> LEAD_QUANTILE      HYP        ALC        DBP1      DBP2
#> 0.0000000 0.0000000 0.026867 0.060035 0.063905
#>      DBP3       DBP4        SBP1        SBP2      SBP3
#> 0.070974 0.891124 0.060035 0.063905 0.070942
#>      SBP4
#> 0.891124

nhanes_df <- na.omit(subset(NHANESsample,
                             select= -c(SBP2, SBP3, SBP4, DBP2, DBP3, DBP4)))
```

In the last chapter, we introduced the `table()` and `summary()` functions to quickly summarize categorical and quantitative vectors. We can observe that over half of the observations never smoked and that the most recent NHANES cycle in the data is 2017-2018.

```
table(nhanes_df$SMOKE)
#>
#> NeverSmoke  QuitSmoke StillSmoke
#> 13774        8019     6799
summary(nhanes_df$YEAR)
#>   Min. 1st Qu. Median   Mean 3rd Qu.   Max.
#> 1999    2003   2007 2008    2011 2017
```

We decide to select the most recent observations from NHANES 2017-2018 for our analysis in this chapter. We use the `subset()` function to select these rows.

```
nhanes_df <- subset(nhanes_df, nhanes_df$YEAR==2017)
```

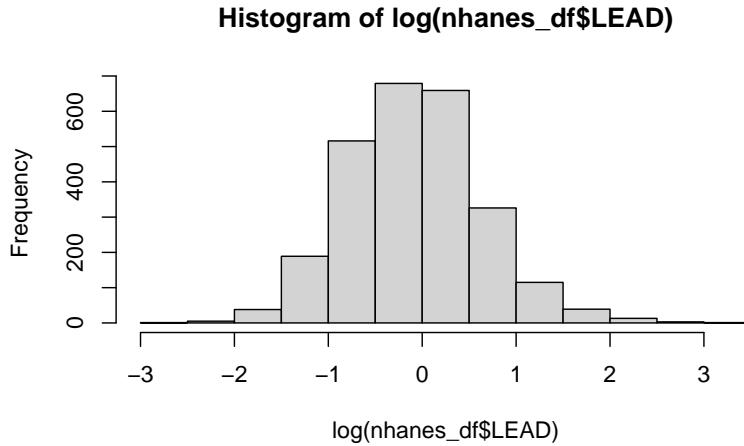
As shown above, smoking status has been coded into three categories: “NeverSmoke”, “QuitSmoke”, and “StillSmoke”. We want to create a new column to represent whether someone has ever smoked. To do so, we use the `ifelse()` function, which allows us to create

a new vector using logic. The logic captured by this function is that we will take one value if we meet some condition(s) and we will take a second value otherwise. The first argument is a vector of TRUE/FALSE values representing the conditions, the next argument is the value to use if we meet the condition(s), and the last argument is the value to use otherwise. We use this function to create a new vector EVER\_SMOKE that is equal to “Yes” for those who are either still smoking or quit smoking and equal to “No” otherwise.

```
nhanes_df$EVER_SMOKE <- ifelse(nhanes_df$SMOKE %in% c("QuitSmoke", "StillSmoke"),
                                  "Yes", "No")
table(nhanes_df$EVER_SMOKE)
#>
#>   No   Yes
#> 1411 1173
```

The `summary()` and `table()` functions allow us to summarize the univariate sample distributions of columns. We may also want to plot these distributions. We saw in Chapter 3 that the `hist()` function creates a histogram plot. Below we use this function to plot a histogram of the log transformation of the lead column.

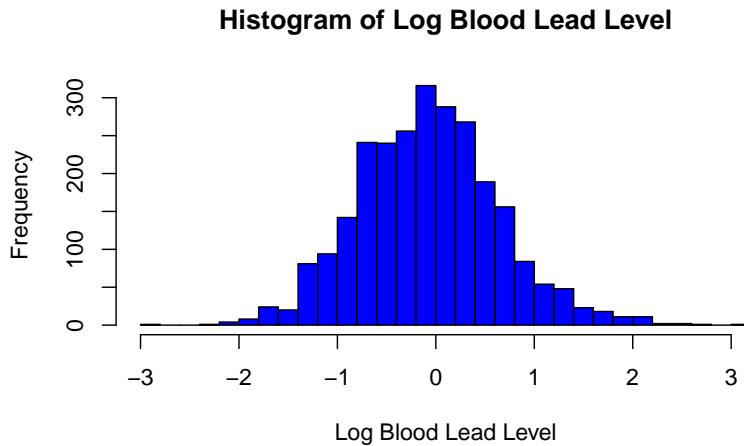
```
hist(log(nhanes_df$LEAD))
```



If we want to polish this figure, we can use some of the other optional arguments to the `hist()` function. For example, we may want to update the text `log(nhanes_df$lead)` in the title and x-axis. Below, we update the `color`, labels, and number of bins for the plot. The argument `breaks` specifies the number of bins to use to create the histogram, `col` specifies the color, `main`

specifies the title of the plot, and `xlab` specifies the x-axis label (using `ylab` would specify the y-axis label). Read the documentation `?hist` for the full list of arguments available.

```
hist(log(nhanes_df$LEAD), breaks = 30, col="blue",
      main="Histogram of Log Blood Lead Level",
      xlab="Log Blood Lead Level")
```



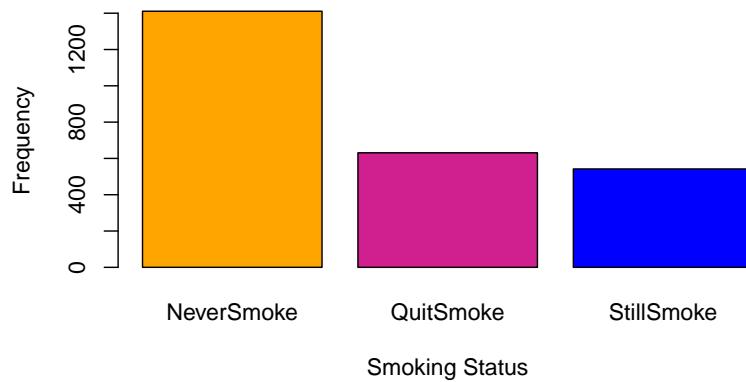
For categorical columns, we may want to plot the counts in each category using a bar plot. The function `barplot()` asks us to specify the `names` and `heights` of the bars. To do so, we will need to store the counts for each category. Again, we update the color and labels.

```
smoke_counts <- table(nhanes_df$SMOKE)
barplot(height=smoke_counts, names=names(smoke_counts), col="violetred",
        xlab="Smoking Status", ylab="Frequency")
```



With a bar plot, we can even specify a different color for each bar. To do so, `col` must be a vector of specified colors with the same length as the number of categories.

```
barplot(height=smoke_counts, names=names(smoke_counts),
        col=c("orange","violetred","blue"),
        xlab="Smoking Status", ylab="Frequency")
```



#### 4.1.1 Practice Question

Recreate the following barplot of the percentage of values in each `LEAD_QUANTILE` category:

```
# Insert your solution here:
```

## 4.2 Bivariate Distributions

We now turn our attention to relationships among multiple columns. When we have two categorical columns, we can use the `table()` function to find the counts across all combinations. For example, below we look at the distribution of smoking status levels by sex. We observe that a higher percentage of female participants have never smoked.

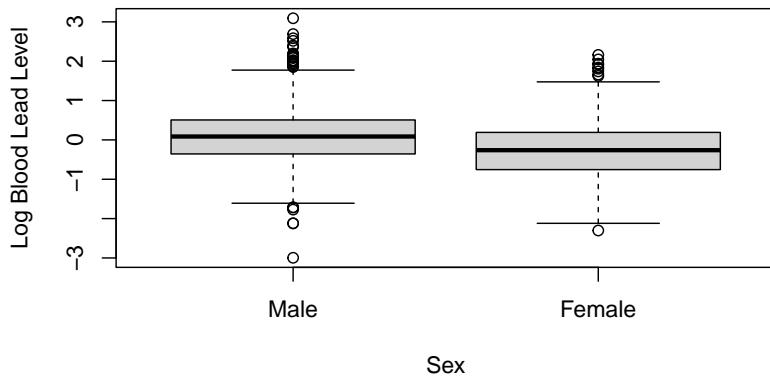
```
table(nhanes_df$SMOKE, nhanes_df$SEX)
#>
#>           Male Female
#> NeverSmoke  596   815
#> QuitSmoke   390   241
#> StillSmoke  324   218
```

To look at the sample distribution of a continuous column stratified by a categorical column, we could call the `summary()` function for each subset of the data. Below we look at the distribution of blood lead level by sex and observe higher blood lead levels in male observations.

```
summary(nhanes_df$LEAD[nhanes_df$SEX=="Female"])
#>   Min. 1st Qu. Median   Mean 3rd Qu.   Max.
#>  0.10    0.47   0.77   0.98   1.21   8.67
summary(nhanes_df$LEAD[nhanes_df$SEX=="Male"])
#>   Min. 1st Qu. Median   Mean 3rd Qu.   Max.
#>  0.05    0.70   1.09   1.46   1.66  22.01
```

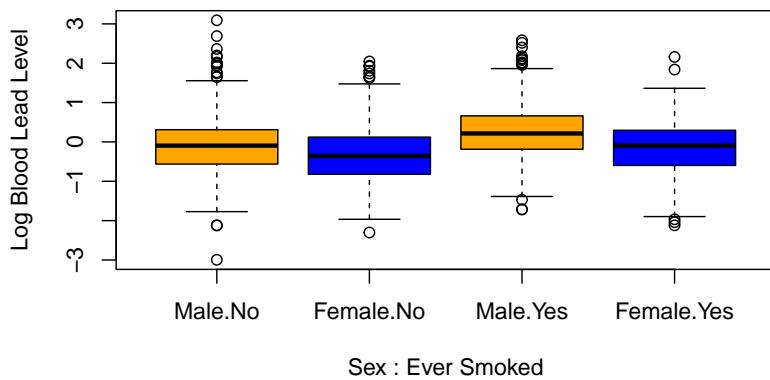
We could also observe this visually through a box plot. When given one categorical column and one continuous column, the `plot()` function creates a box plot. By default, the first argument is the x-axis and second argument is the y-axis.

```
plot(nhanes_df$SEX, log(nhanes_df$LEAD), ylab="Log Blood Lead Level",
      xlab="Sex")
```



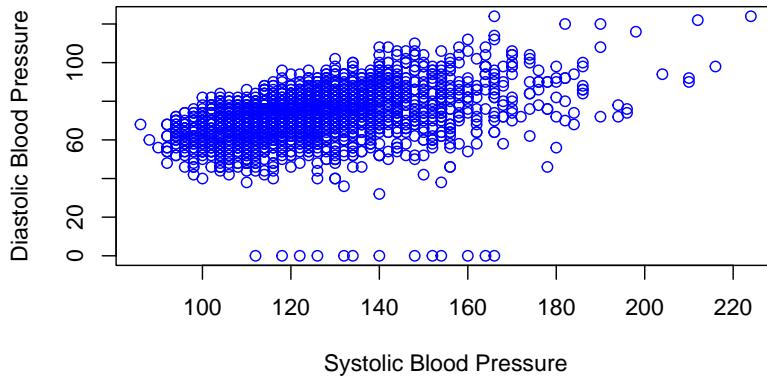
Alternatively, we could use the `boxplot()` function, which can be passed a formula. A formula is a string representation of how to group the data, where the left hand side is the continuous column and the right hand side is one or more categorical columns to group by. In the case below, we group by multiple columns, `SEX` and `EVER_SMOKE`, so our formula is `log(LEAD)~SEX+EVER_SMOKE`. The second argument to the function specifies the data. We specify the column colors to show the link between the box plots shown.

```
boxplot(log(LEAD)~SEX+EVER_SMOKE, data=nhanes_df,
        col=c("orange", "blue", "orange", "blue"),
        xlab="Sex : Ever Smoked", ylab = "Log Blood Lead Level")
```



To visualize the bivariate distributions between two continuous columns, we can use scatter plots. To create a scatter plot, we use the `plot()` function again. Below, we use this function to show the relationship between systolic and diastolic blood pressure.

```
plot(nhanes_df$SBP1, nhanes_df$DBP1, col="blue", xlab="Systolic Blood Pressure",
      ylab="Diastolic Blood Pressure")
```



The two measures of blood pressure look highly correlated. We can calculate their Pearson and Spearman correlation using the `cor()` function. The default method is the Pearson correlation, but we can also calculate the Kendall or Spearman correlation by specifying the method.

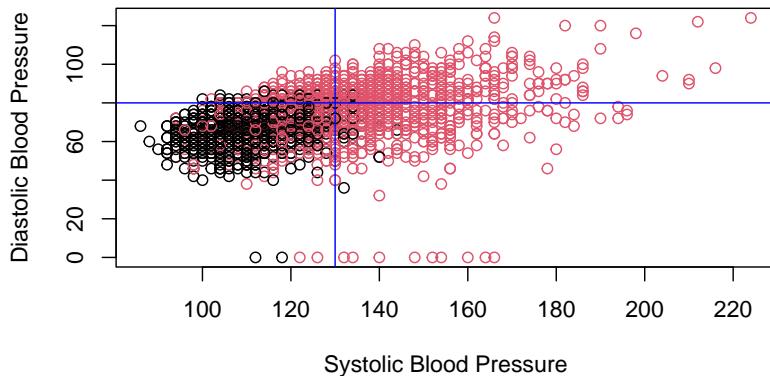
```
cor(nhanes_df$SBP1, nhanes_df$DBP1)
#> [1] 0.417
cor(nhanes_df$SBP1, nhanes_df$DBP1, method="spearman")
#> [1] 0.471
```

We may also want to add some extra information to our plot above. This time, instead of specifying the color manually, we use the column `hyp`, an indicator for hypertension, to specify the color. We have to make sure this vector is a factor for R to color by group. Additionally, we add a blue vertical and horizontal line using the `abline()` function to mark cutoffs for hypertension. Even though this function is called after `plot()`, the lines are automatically added to the current plot. We can see that most of those with hypertension have systolic or diastolic blood pressure measurements above this threshold.

```

plot(nhanes_df$SBP1, nhanes_df$DBP1, col=as.factor(nhanes_df$HYP),
      xlab="Systolic Blood Pressure",
      ylab="Diastolic Blood Pressure")
abline(v=130, col="blue")
abline(h=80, col="blue")

```



The plots above are all displayed as a single figure. If we want to display multiple plots next to each other, we can specify the graphical parameters using the `par()` function by updating the argument `mfrow=c(nrow, ncol)` with the number of columns and rows we would like to use for our figures. Below, we use this to display the distribution of log blood lead level between those with and without hypertension next to the plot from above.

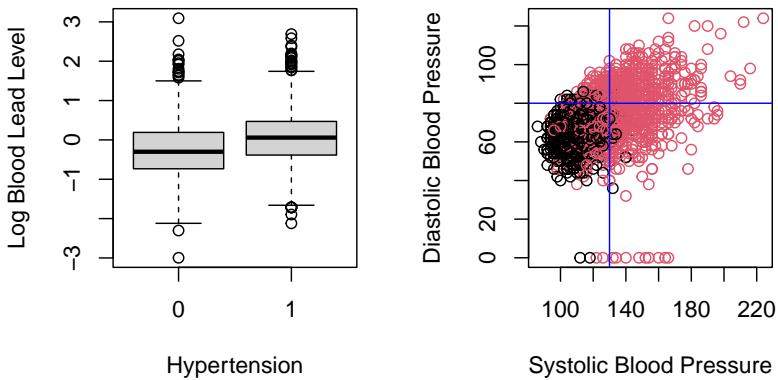
```

par(mfrow=c(1,2))

# boxplot
boxplot(log(LEAD)~HYP, data=nhanes_df, xlab="Hypertension", ylab="Log Blood Lead Level")

# scatterplot
plot(nhanes_df$SBP1, nhanes_df$DBP1, col=as.factor(nhanes_df$HYP),
      xlab="Systolic Blood Pressure",
      ylab="Diastolic Blood Pressure")
abline(v=130, col="blue")
abline(h=80, col="blue")

```



We then reset to only display a single plot for future images using the `par()` function again.

```
par(mfrow=c(1,1))
```

#### 4.2.1 Practice Question

Recreate these three boxplots (one for each education level) of income by BMI category and arrange them next to each other using the `par()` function.

```
# Insert your solution here:
```

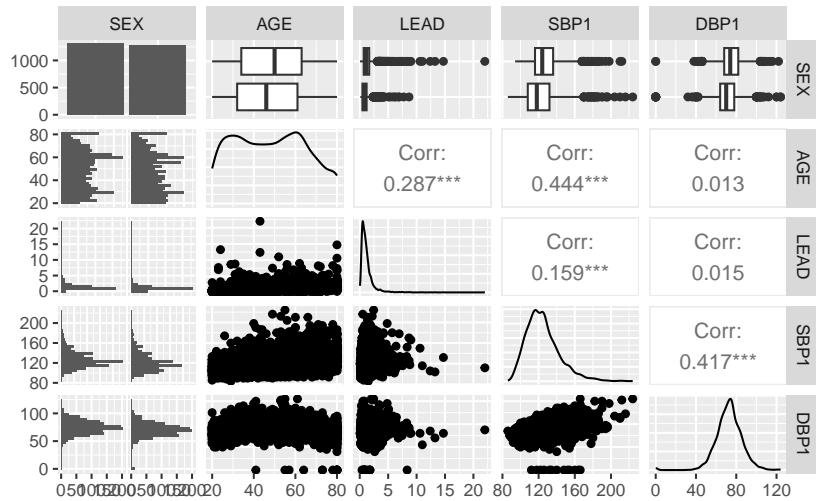
### 4.3 Autogenerated Plots

Above, we learned some new functions for visualizing the relationship between columns. The `GGally` package contains some useful functions for looking at multiple univariate and bivariate relationships at the same time, such as the `ggpairs()` function. `ggpairs()` takes the data as its first argument. By default, it will plot the pairwise distributions for all columns, but we can also specify to only select a subset of columns using the `columns` argument. You can see below that it plots bar plots and density plots for each univariate sample distribution. It then plots the bivariate distributions and calculates the Pearson correlation for all pairs of continuous columns. That's a lot of information!

```

ggpairs(nhanes_df, columns = c("SEX", "AGE", "LEAD", "SBP1", "DBP1"))
#> `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
#> `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
#> `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
#> `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

```

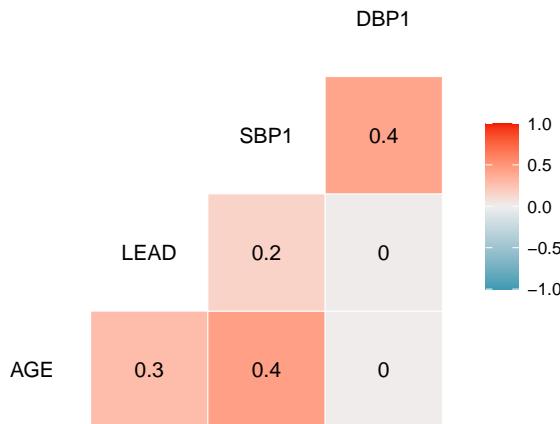


Another useful function in this package is the `ggcorr()` function: this function takes in a data frame with only numeric columns and displays the correlation between all pairs of columns, where the color of each grid cell indicates the strength of the correlation. The additional argument `label=TRUE` prints the actual correlation value on each grid cell. This is a useful way to identify pairs of strongly correlated columns.

```

nhanes_cont <- nhanes_df[,c("AGE", "LEAD", "SBP1", "DBP1")]
ggcorr(nhanes_cont, label=TRUE)

```



## 4.4 Tables

Another useful way to display information about your data is through tables. For example, it is standard practice in articles to have the first table in the paper give information about the study sample, such as the mean and standard deviation for all continuous columns and the proportions for categorical columns. The `gt` package is designed to create polished tables that can include footnotes, titles, column labels, etc. The `gtsummary` package is an extension of this package that can create summary tables. We will focus on the latter but come back to creating nice tables in Chapter 12.

To start, we create a `gt` object (a special type of table) of the first six rows of our data using the `gt()` function. In R Markdown, the table would be automatically displayed nicely when `knit`. Since we are using this within a Jupyter notebook, however, we need to pass this to another function to make sure it displays correctly as HTML. The pipe operator `%>%` passes the result on the left hand side as the first argument to the function on the right hand side. You can see the difference in the formatting as opposed to printing the data.

```
gt(head(nhanes_df)) %>% gt:::as.tags.gt_tbl()
```

ID	AGE	SEX	RACE	EDUCATION	INCOME	SMOKE	YEAR	LEAD	DBP1
93711	56	Male	Other Race	MoreThanHS	5.00	NeverSmoke	2017	2.15	0.4
93713	67	Male	Non-Hispanic White	HS	2.65	StillSmoke	2017	3.71	0.2
93716	61	Male	Other Race	MoreThanHS	5.00	QuitSmoke	2017	1.99	0
93717	22	Male	Non-Hispanic White	HS	1.49	StillSmoke	2017	1.93	0
93721	60	Female	Mexican American	LessThanHS	3.04	NeverSmoke	2017	0.75	0.3

ID	AGE	SEX	RACE	EDUCATION	INCOME	SMOKE	YEAR	LEAD	
93722	60	Female	Non-Hispanic White	MoreThanHS	2.07	NeverSmoke	2017	0.98	

We will now show you how to use the `tbl_summary()` function in the `gtsummary` package. The first argument to this function is again the data frame. By default, this function will summarize all the columns in the data. Instead, we use the `include` argument to specify a list of columns to include. We then pipe this result to `as_gt()` which creates a gt table from the summary output. Again, we then need to pass this to `gt:::as.tags.gt_tbl()` to display this table as HTML within a Jupyter notebook. Note that the table computes the total number of observations and the proportions for categorical columns and the median and interquartile range for continuous columns.

```
tbl_summary(nhanes_df, include= c("SEX", "RACE", "AGE", "EDUCATION", "SMOKE",
                                "BMI_CAT", "LEAD", "SBP1", "DBP1", "HYP")) %>%
  as_gt() %>%
  gt:::as.tags.gt_tbl()
```

Characteristic	N = 2,584 <sup>1</sup>
SEX	
Male	1,310 (51%)
Female	1,274 (49%)
RACE	
Mexican American	358 (14%)
Other Hispanic	225 (8.7%)
Non-Hispanic White	992 (38%)
Non-Hispanic Black	568 (22%)
Other Race	441 (17%)
AGE	48 (33, 62)
EDUCATION	
LessThanHS	373 (14%)
HS	593 (23%)
MoreThanHS	1,618 (63%)
SMOKE	
NeverSmoke	1,411 (55%)
QuitSmoke	631 (24%)
StillSmoke	542 (21%)
BMI_CAT	
BMI<=25	663 (26%)
25<BMI<30	808 (31%)
BMI>=30	1,113 (43%)

Characteristic	N = 2,584 <sup>1</sup>
LEAD	0.93 (0.56, 1.44)
SBP1	122 (112, 134)
DBP1	72 (66, 80)
HYP	1,451 (56%)

<sup>1</sup>  
n  
(%);  
Me-  
dian  
(IQR)

We can update our table by changing some of its arguments. This time, we specify that we want to stratify our table by hypertension status so that the table summarizes the data by this grouping. Additionally, we change how continuous columns are summarized by specifying that we want to report the mean and standard deviation instead of the median and interquartile range. We do this using the `statistic` argument. The documentation for the `tbl_summary()` function can help you format this argument depending on which statistics you would like to display.

```
tbl_summary(nhanes_df, include= c("SEX", "RACE", "AGE", "EDUCATION", "SMOKE",
                                "BMI_CAT", "LEAD", "SBP1", "DBP1", "HYP"),
            by = "HYP", statistic = list(all_continuous() ~ "{mean} ({sd})")) %>%
  as_gt() %>%
  gt:::as.tags.gt_tbl()
```

Characteristic	0, N = 1,133 <sup>1</sup>	1, N = 1,451 <sup>1</sup>
SEX		
Male	472 (42%)	838 (58%)
Female	661 (58%)	613 (42%)
RACE		
Mexican American	186 (16%)	172 (12%)
Other Hispanic	104 (9.2%)	121 (8.3%)
Non-Hispanic White	429 (38%)	563 (39%)
Non-Hispanic Black	203 (18%)	365 (25%)
Other Race	211 (19%)	230 (16%)
AGE	40 (15)	55 (16)
EDUCATION		
LessThanHS	151 (13%)	222 (15%)
HS	250 (22%)	343 (24%)

Characteristic	0, N = 1,133 <sup>1</sup>	1, N = 1,451 <sup>1</sup>
MoreThanHS	732 (65%)	886 (61%)
SMOKE		
NeverSmoke	678 (60%)	733 (51%)
QuitSmoke	220 (19%)	411 (28%)
StillSmoke	235 (21%)	307 (21%)
BMI_CAT		
BMI<=25	392 (35%)	271 (19%)
25<BMI<30	351 (31%)	457 (31%)
BMI>=30	390 (34%)	723 (50%)
LEAD	1.03 (1.15)	1.37 (1.25)
SBP1	112 (10)	134 (18)
DBP1	67 (9)	77 (14)

<sup>1</sup> n  
(%);  
Mean  
(SD)

Outside of the `gt` and `gtsummary` packages, another common package used to create summary tables is the [tableone package](#), which is not covered in this book.

## 4.5 Recap Video

<https://www.youtube.com/embed/Kdc6x-bDfso>

## 4.6 Exercises

For these exercises, we will continue using the `nhanes_df` data.

1. Using both numerical and graphical summaries, describe the distribution of the first diastolic blood pressure reading `DBP1` among study participants. Then, create a column called `INCOME_CAT` with two categories: “low” for those whose income is at most 2 and “not low” otherwise and examine the bivariate distribution of `DBP1` and `INCOME_CAT`. Arrange the two plots next to each other. What do you notice?
2. Subset the data to adults between the ages of 20 and 55. Then, explore how blood pressure varies by age and gender among this age group. Is there a visible trend in blood pressure with increasing age among either sex?

3. For males between the ages of 50-59, compare blood pressure across race as reported in the race column. Then, create a summary table stratified by the race column and report the mean, standard deviation, minimum and maximum values for all continuous columns.
4. Recreate the following two plots in R. Based on what you see, how do you expect blood lead levels to change by year? Check your answer to the previous question by plotting these two columns against each other.

# 5 Data Transformations and Summaries

In this chapter, we will introduce the `dyplr` package, which is part of the `tidyverse` group of packages, to expand our tools in exploring and transforming our data. We will learn how to do some basic manipulations of data (e.g. adding or removing columns, filtering data, arranging by one or multiple columns) as well as how to summarize data (e.g. grouping by values, calculating summary statistics). We will also practice combining these operations using the pipe operator `%>%`. We will use the same sample of the National Health and Nutrition Examination Survey ([NHANES](#)) as in [Chapter 4](#).

```
suppressPackageStartupMessages(library(HDSinRdata))
suppressPackageStartupMessages(library(tidyverse))
data(NHANESsample)
```

## 5.1 Tibbles and Data Frames

Take a look at the class of `NHANESsample`. As we might expect, the data is stored as a data frame.

```
class(NHANESsample)
#> [1] "data.frame"
```

However, the `tidyverse` also works with another data structure called a **tibble**. A **tibble** has all the properties of data frames that we have learned so far, but they are a more modern version of a data frame. To convert our data to this data structure we use the `as_tibble()` function. In practice, there are only very slight difference between the two data structures, and you generally do not need to convert data frames to tibbles. Below we convert our data from a data frame to a tibble and print the head of the data before converting it back to a data frame and repeating. You can see the two structures have a slightly different print statement but are otherwise very similar.

```
nhanes_df <- as_tibble(NHANESsample)
print(head(nhanes_df))
#> # A tibble: 6 x 21
```

```

#>      ID AGE SEX RACE EDUCATION INCOME SMOKE YEAR LEAD BMI_CAT
#> <dbl> <dbl> <fct> <fct> <fct> <dbl> <fct> <dbl> <dbl> <fct>
#> 1 2 77 Male Non-Hisp~ MoreThan~ 5 Neve~ 1999 5 BMI<=25
#> 2 5 49 Male Non-Hisp~ MoreThan~ 5 Quit~ 1999 1.6 25<BMI~
#> 3 12 37 Male Non-Hisp~ MoreThan~ 4.93 Neve~ 1999 2.4 BMI>=30
#> 4 13 70 Male Mexican ~ LessThan~ 1.07 Quit~ 1999 1.6 25<BMI~
#> 5 14 81 Male Non-Hisp~ LessThan~ 2.67 Stil~ 1999 5.5 25<BMI~
#> # i 1 more row
#> # i 11 more variables: LEAD_QUANTILE <fct>, HYP <dbl>, ALC <chr>,
#> # DBP1 <dbl>, DBP2 <dbl>, DBP3 <dbl>, DBP4 <dbl>, SBP1 <dbl>,
#> # SBP2 <dbl>, SBP3 <dbl>, SBP4 <dbl>

nhanes_df <- as.data.frame(nhanes_df)
print(head(nhanes_df))
#>   ID AGE   SEX          RACE EDUCATION INCOME       SMOKE YEAR
#> 1 2 77 Male Non-Hispanic White MoreThanHS 5.00 NeverSmoke 1999
#> 2 5 49 Male Non-Hispanic White MoreThanHS 5.00 QuitSmoke 1999
#> 3 12 37 Male Non-Hispanic White MoreThanHS 4.93 NeverSmoke 1999
#> 4 13 70 Male Mexican American LessThanHS 1.07 QuitSmoke 1999
#> 5 14 81 Male Non-Hispanic White LessThanHS 2.67 StillSmoke 1999
#> 6 15 38 Female Non-Hispanic White MoreThanHS 4.52 StillSmoke 1999
#>   LEAD BMI_CAT LEAD_QUANTILE HYP ALC DBP1 DBP2 DBP3 DBP4 SBP1 SBP2
#> 1 5.0 BMI<=25             Q4 0 Yes 58 56 56 NA 106 98
#> 2 1.6 25<BMI<30          Q3 1 Yes 82 84 82 NA 122 122
#> 3 2.4 BMI>=30            Q4 1 Yes 108 98 100 NA 182 172
#> 4 1.6 25<BMI<30          Q3 1 Yes 78 62 70 NA 140 130
#> 5 5.5 25<BMI<30          Q4 1 Yes 56 NA 58 64 142 NA
#> 6 1.5 25<BMI<30          Q3 0 Yes 68 68 70 NA 106 112
#>   SBP3 SBP4
#> 1 98 NA
#> 2 122 NA
#> 3 176 NA
#> 4 130 NA
#> 5 134 138
#> 6 106 NA

```

We mention tibbles here since some functions in the `tidyverse` package convert data frames to tibbles in their output. In particular, when we summarize over groups below we can expect a tibble to be returned. It is useful to be aware that our data may change data structure with such functions and to know that we can always convert back if needed.

## 5.2 Subsetting Data

In earlier chapters, we have seen how to select and filter data using row and column indices as well as using the `subset()` function. The `dplyr` package has its own functions that are useful to subset the data. The `select()` function allows us to select a subset of columns: this function takes in the data frame (or tibble) and the names or indices of the columns we want to select. For example, if we only wanted to select the variables for race and blood lead level, we could specify these two columns. To display the result of this selection, we use the pipe operator `%>%`. Recall that this takes the result on the left hand side and passes it as the first argument to the function on the right hand side. The output below shows that there are only two columns in the filtered data.

```
select(nhanes_df, c(RACE, LEAD)) %>% head()
#>          RACE LEAD
#> 1 Non-Hispanic White  5.0
#> 2 Non-Hispanic White  1.6
#> 3 Non-Hispanic White  2.4
#> 4 Mexican American   1.6
#> 5 Non-Hispanic White  5.5
#> 6 Non-Hispanic White  1.5
```

The `select()` function can also be used to *remove* columns by adding a negative sign in front of the vector of column names in its arguments. For example, below we keep all columns except `ID` and `LEAD_QUANTILE`. Note that in this case we have saved the selected data back to our data frame `nhanes_df`. Additionally, this time we used a pipe operator to pipe the data to the `select` function itself.

```
nhanes_df <- nhanes_df %>% select(-c(ID, LEAD_QUANTILE))
names(nhanes_df)
#> [1] "AGE"        "SEX"         "RACE"        "EDUCATION"   "INCOME"
#> [6] "SMOKE"      "YEAR"        "LEAD"        "BMI_CAT"     "HYP"
#> [11] "ALC"        "DBP1"        "DBP2"        "DBP3"        "DBP4"
#> [16] "SBP1"       "SBP2"        "SBP3"        "SBP4"
```

While `select()` allows us to choose a subset of columns, the `filter()` function allows us to choose a subset of rows. The `filter()` function takes a data frame as the first argument and a vector of booleans as the second argument. This vector of booleans can be generated using conditional statements as we used in [Chapter 4](#). Below, we choose to filter the data to only observations after 2008.

```
nhanes_df_recent <- nhanes_df %>% filter(YEAR >= 2008)
```

We can combine conditions by using multiple `filter` calls, by creating a more complicated conditional statement using the `&` (and), `|` (or), and `%in%` (in) operators, or by separating the conditions with commas within `filter`. Below, we demonstrate these three ways to filter the data to males between 2008 and 2012. Note that the `between()` function allows us to capture the logic `YEAR >= 2008 & YEAR <= 2012`.

```
# Example 1: multiple filter calls
nhanes_df_males1 <- nhanes_df %>%
  filter(YEAR <= 2012) %>%
  filter(YEAR >= 2008) %>%
  filter(SEX == "Male")

# Example 2: combine with & operator
nhanes_df_males2 <- nhanes_df %>%
  filter((YEAR <= 2012) & (YEAR >= 2008) & (SEX == "Male"))

# Example 3: combine into one filter call with commas
nhanes_df_males3 <- nhanes_df %>%
  filter(between(YEAR, 2008, 2012), SEX == "Male")
```

The use of parentheses in the code above is especially important in order to capture our desired logic. In all these examples, we broke our code up into multiple lines, which makes it easier to read. A good rule of thumb is to not go past 80 characters in a line, and R Studio conveniently has a vertical gray line at this limit. To create a new line, you can hit enter either after an operator (e.g. `%>%`, `+`, `|`) or within a set of unfinished brackets or parentheses. Either of these breaks lets R know that your code is not finished yet.

Lastly, we can subset the data using the `slice()` function to select a slice of rows by their index. The function takes in the data set and a vector of indices. Below, we find the first and last rows of the data.

```
slice(nhanes_df, c(1, nrow(nhanes_df)))
#>   AGE  SEX          RACE EDUCATION INCOME      SMOKE YEAR LEAD
#> 1  77 Male Non-Hispanic White MoreThanHS  5.00 NeverSmoke 1999  5.0
#> 2  38 Male Non-Hispanic White MoreThanHS  1.56 StillSmoke 2017  0.9
#>   BMI_CAT HYP ALC DBP1 DBP2 DBP3 DBP4 SBP1 SBP2 SBP3 SBP4
#> 1 BMI<=25    0 Yes   58   56   56   NA  106   98   98   NA
#> 2 BMI>=30    1 Yes   98   92   98   NA  150  146  148   NA
```

A few other useful slice functions are `slice_sample()`, `slice_max()`, and `slice_min()`. The first takes in an argument `n` which specifies the number of *random* rows to sample from the data. For example, we could randomly sample 100 rows from our data. The latter two allow us to specify a column through the argument `order_by` and return the `n` rows with either the

highest or lowest values in that column. Below we find the three male observations from 2007 with the highest and lowest blood lead levels and select a subset of columns to display.

```
# three male observations with highest blood lead level in 2007  
nhanes_df %>%  
  filter(YEAR == 2007, SEX == "Male") %>%  
  select(c(RACE, EDUCATION, SMOKE, LEAD, SBP1, DBP1)) %>%  
  slice_max(order_by = LEAD, n=3)  
#>          RACE EDUCATION      SMOKE LEAD SBP1 DBP1  
#> 1 Non-Hispanic Black LessThanHS NeverSmoke 33.1 106   66  
#> 2     Other Hispanic LessThanHS StillSmoke 26.8 106   72  
#> 3     Other Hispanic LessThanHS StillSmoke 25.7 112   60  
  
# three male observations with lowest blood lead level in 2007  
nhanes_df %>%  
  filter(YEAR == 2007, SEX == "Male") %>%  
  select(c(RACE, EDUCATION, SMOKE, LEAD, SBP1, DBP1)) %>%  
  slice_min(order_by = LEAD, n=3)  
#>          RACE EDUCATION      SMOKE LEAD SBP1 DBP1  
#> 1 Non-Hispanic White LessThanHS NeverSmoke 0.177 114   80  
#> 2     Other Hispanic LessThanHS QuitSmoke 0.280 122   62  
#> 3 Mexican American MoreThanHS QuitSmoke 0.320 112   66
```

### 5.2.1 Practice Question

Filter the data to only those with an education level of more than HS who report alcohol use. Then, select only the diastolic blood pressure variables and display the 4th and 10th rows. Your result should match the data below.

```
# Insert your solution here:
```

## 5.3 Updating Rows and Columns

The next few functions we will look at will allow us to update the rows and columns in our data. For example, the `rename()` function allows us to change the names of columns. Below, we change the name of `INCOME` to `PIR` since this variable is the poverty income ratio and also update the name of `SMOKE` to be `SMOKE_STATUS`. When specifying these names, the new name is on the left of the `=` and the old name is on the right.

```

nhanes_df <- nhanes_df %>% rename(PIR = INCOME, SMOKE_STATUS = SMOKE)
names(nhanes_df)
#> [1] "AGE"          "SEX"           "RACE"          "EDUCATION"
#> [5] "PIR"          "SMOKE_STATUS"  "YEAR"          "LEAD"
#> [9] "BMI_CAT"      "HYP"           "ALC"           "DBP1"
#> [13] "DBP2"         "DBP3"          "DBP4"          "SBP1"
#> [17] "SBP2"         "SBP3"          "SBP4"

```

In the last chapter, we created a new variable called `EVER_SMOKE` based on the smoking status variable using the `ifelse()` function. Recall that this function allows us to specify a condition and then two alternative values based on whether we meet or do not meet this condition. We see that there are about 15,000 subjects in our data who never smoked.

```

ifelse(nhanes_df$SMOKE_STATUS == "NeverSmoke", "No", "Yes") %>% table()
#> .
#>   No    Yes
#> 15087 16178

```

Another useful function from the tidyverse is the `case_when()` function, which is an extension of the `ifelse()` function but allows to specify more than two cases. We demonstrate this function below to show how we could relabel the levels of the `SMOKE_STATUS` column. For each condition, we use the right side of the `~` to specify the value associated with a TRUE for that condition.

```

case_when(nhanes_df$SMOKE_STATUS == "NeverSmoke" ~ "Never Smoked",
          nhanes_df$SMOKE_STATUS == "QuitSmoke" ~ "Quit Smoking",
          nhanes_df$SMOKE_STATUS == "StillSmoke" ~ "Current Smoker") %>% table()
#> .
#> Current Smoker  Never Smoked  Quit Smoking
#>            7317        15087        8861

```

Above, we did not store the columns we created. To do so, we could use the `$` operator or the `cbind()` function. The tidyverse also includes an alternative function to add columns called `mutate()`. This function takes in a data frame and a set of columns with associated names to add to the data or update. In the example below, we create the column `EVER_SMOKE` and update the column `SMOKE_STATUS`. Within the `mutate()` function, we do not have to use the `$` operator to reference the column `SMOKE_STATUS`. Instead, we can specify just the column name and it will interpret it as that column.

```

nhanes_df <- nhanes_df %>%
  mutate(EVER_SMOKE = ifelse(SMOKING_STATUS == "NeverSmoke", "No", "Yes"),

```

```

SMOKE_STATUS = case_when(SMOKE_STATUS == "NeverSmoke" ~ "Never Smoked",
                        SMOKE_STATUS == "QuitSmoke" ~ "Quit Smoking",
                        SMOKE_STATUS == "StillSmoke" ~ "Current Smoker"))

```

The last function we will demonstrate in this section is the `arrange()` function, which takes in a data frame and a vector of columns used to sort the data (data is sorted by the first column with ties being sorted by the second column, etc.). By default, the `arrange()` function sorts the data in increasing order, but we can use the `desc()` function to instead sort in descending order. For example, the code below filters the data to male smokers before sorting by decreasing systolic and diastolic blood pressure in descending order.

```

nhanes_df %>%
  select(c(YEAR, SEX, SMOKE_STATUS, SBP1, DBP1, LEAD)) %>%
  filter(SEX == "Male", SMOKE_STATUS == "Current Smoker") %>%
  arrange(desc(SBP1), desc(DBP1)) %>%
  head(10)
#>   YEAR   SEX   SMOKE_STATUS SBP1  DBP1 LEAD
#> 1  2011 Male Current Smoker  230   120 5.84
#> 2  2015 Male Current Smoker  230    98 1.56
#> 3  2009 Male Current Smoker  220    80 4.84
#> 4  2001 Male Current Smoker  218   118 3.70
#> 5  2017 Male Current Smoker  212   122 2.20
#> 6  2003 Male Current Smoker  212    54 4.00
#> 7  2011 Male Current Smoker  210   92 5.37
#> 8  2007 Male Current Smoker  210    80 2.18
#> 9  2015 Male Current Smoker  206   108 1.44
#> 10 2003 Male Current Smoker  206    68 1.80

```

### 5.3.1 Practice Question

Create a new column called `DBP_CHANGE` that is equal to the difference between a patient's first and fourth diastolic blood pressure readings. Then, sort the data frame by this new column in increasing order and print the first four rows. The first four `DBP_CHANGE` values in the head of the resulting dataset should be -66, -64, -64, and -62.

```
# Insert your solution here:
```

## 5.4 Summarizing and Grouping

If we wanted to understand how many observations there are for each given race category, we could use the `table()` function as we described in earlier chapters. Another similar function is the `count()` function. This function takes in a data frame and one or more columns and counts the number of rows for each combination of unique values in these columns. If no columns are specified, it counts the total number of rows in the data frame. Below, we find the total number of rows (31,265) and the number of observations by race and year. We can see that the number in each group fluctuates quite a bit!

```
count(nhances_df)
#>      n
#> 1 31265
count(nhances_df, RACE, YEAR)
#>          RACE YEAR     n
#> 1 Mexican American 1999 713
#> 2 Mexican American 2001 674
#> 3 Mexican American 2003 627
#> 4 Mexican American 2005 634
#> 5 Mexican American 2007 639
#> 6 Mexican American 2009 672
#> 7 Mexican American 2011 322
#> 8 Mexican American 2013 234
#> 9 Mexican American 2015 287
#> 10 Mexican American 2017 475
#> 11 Other Hispanic 1999 181
#> 12 Other Hispanic 2001 129
#> 13 Other Hispanic 2003 80
#> 14 Other Hispanic 2005 96
#> 15 Other Hispanic 2007 395
#> 16 Other Hispanic 2009 367
#> 17 Other Hispanic 2011 337
#> 18 Other Hispanic 2013 167
#> 19 Other Hispanic 2015 214
#> 20 Other Hispanic 2017 313
#> 21 Non-Hispanic White 1999 1401
#> 22 Non-Hispanic White 2001 1882
#> 23 Non-Hispanic White 2003 1785
#> 24 Non-Hispanic White 2005 1818
#> 25 Non-Hispanic White 2007 1940
#> 26 Non-Hispanic White 2009 2169
```

```

#> 27 Non-Hispanic White 2011 1463
#> 28 Non-Hispanic White 2013 917
#> 29 Non-Hispanic White 2015 685
#> 30 Non-Hispanic White 2017 1413
#> 31 Non-Hispanic Black 1999 463
#> 32 Non-Hispanic Black 2001 542
#> 33 Non-Hispanic Black 2003 576
#> 34 Non-Hispanic Black 2005 679
#> 35 Non-Hispanic Black 2007 728
#> 36 Non-Hispanic Black 2009 661
#> 37 Non-Hispanic Black 2011 876
#> 38 Non-Hispanic Black 2013 357
#> 39 Non-Hispanic Black 2015 351
#> 40 Non-Hispanic Black 2017 808
#> 41 Other Race 1999 76
#> 42 Other Race 2001 88
#> 43 Other Race 2003 109
#> 44 Other Race 2005 122
#> 45 Other Race 2007 123
#> 46 Other Race 2009 175
#> 47 Other Race 2011 475
#> 48 Other Race 2013 223
#> 49 Other Race 2015 209
#> 50 Other Race 2017 595

```

Finding the counts like we did above is a form of a summary statistic for our data. The `summarize()` function in the tidyverse is used to compute summary statistics of the data and allows us to compute multiple statistics: this function takes in a data frame and one or more summary functions based on the given column names. In the example below, we find the total number of observations as well as the mean and median systolic blood pressure for Non-Hispanic Blacks. Note that the `n()` function is the function within `summarize()` that finds the number of observations. In the `mean()` and `median()` functions we set `na.rm=TRUE` to remove NAs before computing these values (otherwise we could get NA as our output).

```

nhanes_df %>%
  filter(RACE == "Non-Hispanic Black") %>%
  summarize(TOT = n(), MEAN_SBP = mean(SBP1, na.rm=TRUE),
            MEAN_DBP = mean(DBP1, na.rm=TRUE))
#>     TOT MEAN_SBP MEAN_DBP
#> 1 6041      129      72.6

```

If we wanted to repeat this for the other race groups, we would have to change the arguments to

the `filter()` function each time. To avoid having to repeat our code and/or do this multiple times, we can use the `group_by()` function, which takes a data frame and one or more columns with which to group the data by. Below, we group using the `RACE` variable. When we look at printed output it looks almost the same as it did before except we can see that its class is now a grouped data frame, which is printed at the top. In fact, a grouped data frame (or grouped tibble) acts like a set of data frames: one for each group. If we use the `slice()` function with index 1, it will return the first row for each group.

```
nhanes_df %>%
  group_by(RACE) %>%
  slice(1)
#> # A tibble: 5 x 20
#> # Groups:   RACE [5]
#>   AGE SEX   RACE EDUCATION PIR SMOKE_STATUS YEAR LEAD BMI_CAT
#>   <dbl> <fct> <fct>    <dbl> <chr>        <dbl> <dbl> <fct>
#> 1   70 Male Mexican~ LessThan~  1.07 Quit Smoking 1999  1.6 25<BMI~
#> 2   61 Female Other H~ MoreThan~  3.33 Current Smo~ 1999  2.2 BMI<=25
#> 3   77 Male Non-His~ MoreThan~  5 Never Smoked 1999  5   BMI<=25
#> 4   38 Female Non-His~ HS       0.92 Current Smo~ 1999  1.8 25<BMI~
#> 5   63 Female Other R~ MoreThan~  5 Never Smoked 1999  1.2 BMI<=25
#> # i 11 more variables: HYP <dbl>, ALC <chr>, DBP1 <dbl>, DBP2 <dbl>,
#> #   DBP3 <dbl>, DBP4 <dbl>, SBP1 <dbl>, SBP2 <dbl>, SBP3 <dbl>,
#> #   SBP4 <dbl>, EVER_SMOKE <chr>
```

Grouping data is very helpful in combination with the `summarize()` function. Like with the `slice()` function, `summarize()` will calculate the summary values for each group. We can now find the total number of observations as well as the mean systolic and diastolic blood pressure values for each racial group. Note that the returned summarized data is in a tibble.

```
nhanes_df %>%
  group_by(RACE) %>%
  summarize(TOT = n(), MEAN_SBP = mean(SBP1, na.rm=TRUE),
            MEAN_DBP = mean(DBP1, na.rm=TRUE))
#> # A tibble: 5 x 4
#>   RACE          TOT MEAN_SBP MEAN_DBP
#>   <fct>      <int>    <dbl>    <dbl>
#> 1 Mexican American  5277     124.     70.4
#> 2 Other Hispanic   2279     123.     70.1
#> 3 Non-Hispanic White 15473     125.     70.4
#> 4 Non-Hispanic Black  6041     129.     72.6
#> 5 Other Race       2195     122.     72.6
```

After summarizing, the data is no longer grouped by race. If we ever want to remove the group structure from our data, we can use the `ungroup()` function, which restores the data to a single data frame. After ungrouping by race below, we can see that we get a single observation returned by the `slice()` function.

```
nhanes_df %>%
  select(SEX, RACE, SBP1, DBP1) %>%
  group_by(RACE) %>%
  ungroup() %>%
  arrange(desc(SBP1)) %>%
  slice(1)
#> # A tibble: 1 x 4
#>   SEX      RACE          SBP1   DBP1
#>   <fct>    <fct>        <dbl>  <dbl>
#> 1 Female Non-Hispanic White    270    124
```

### 5.4.1 Practice Question

Create a data frame summarizing the percent of patients with hypertension by smoking status. The result should look like this:

```
# Insert your solution here:
```

## 5.5 Recap Video

<https://www.youtube.com/embed/IeRMFCCuxwc>

## 5.6 Exercises

The following exercises use the `covidcases` dataset from the `HDSinRdata` package. Before completing the exercises, be sure to read the documentation for this data (`?covidcases`).

```
data(covidcases)
```

1. Suppose we are interested in the distribution of weekly cases by state. First, create a new column in `covidcases` called `region` specifying whether each state is in the Northeast, Midwest, South, or West (you can either do this by hand using [this list](#) of which states are in which region or you can use `state.region` from the `datasets` package in R). Then,

create a data frame summarizing the average and standard deviation of the weekly cases for the Northeast.

2. Now, create a data frame with the average and standard deviation summarized for each region rather than for just one selected region as in Question 1. Sort this data frame from highest to lowest average weekly cases. What other information would you need in order to more accurately compare these regions in terms of their average cases?
3. Find the ten counties in the Midwest with the lowest weekly deaths in week 15 of this data ignoring ties (use `?slice_min` to find the argument needed for this). What do you notice about the minimum values? See the data documentation for why we observe these values.
4. Filter the data to between weeks 9 and 20 (around the start of the pandemic), get the total cases per county during that time frame, and then find the county in each state that had the highest number of total cases.

# 6 Merging and Reshaping Data

In this chapter, we continue to look at some of the ways to manipulate data using the tidyverse packages. In particular, we will look at reshaping and merging data frames in order to get the data in the format we want. When reshaping data, we can convert between *wide form* (more columns, fewer rows) and *long form* (fewer columns, more rows). We can also use data pivots to put our data into what is called *tidy form*. Additionally, we will look at combining information from multiple data frames into a single data frame. The key ideas when merging data are to think about what the common information is between the data frames and to consider which values we want to keep.

For this chapter, we will use three data sets. The first data set is `covidcases`, which contains the weekly case and death counts by county in the United States for 2020; the second data set is `mobility`, which contains daily mobility estimates by state in 2020; and the third data set is `lockdowndates`, which contains the start and end dates for statewide stay at home orders. Take a look at the first few rows of each data frame below and read the documentation for the column descriptions.

```
suppressPackageStartupMessages(library(tidyverse))
suppressPackageStartupMessages(library(HDSinRdata))
data(covidcases)
data(lockdowndates)
data(mobility)

head(covidcases)
#> # A tibble: 6 x 5
#> # Groups:   state, county, week [6]
#>   state   county   week weekly_cases weekly_deaths
#>   <chr>   <chr>    <dbl>      <int>        <int>
#> 1 Alabama Autauga     12          3          0
#> 2 Alabama Autauga     13          3          0
#> 3 Alabama Autauga     14          2          1
#> 4 Alabama Autauga     15         11          1
#> 5 Alabama Autauga     16          5          1
#> # i 1 more row
```

```

head(mobility)
#> # A tibble: 6 x 5
#> # Groups:   state [1]
#>   state    date      samples    m50 m50_index
#>   <chr>    <chr>     <int>  <dbl>      <dbl>
#> 1 Alabama 2020-03-01  267652  10.9      76.9
#> 2 Alabama 2020-03-02  287264  14.3      98.6
#> 3 Alabama 2020-03-03  292018  14.2      98.2
#> 4 Alabama 2020-03-04  298704  13.1      89.7
#> 5 Alabama 2020-03-05  288218  14.8     102.
#> # i 1 more row

head(lockdowndates)
#> # A tibble: 6 x 3
#>   State    Lockdown_Start Lockdown_End
#>   <chr>    <chr>        <chr>
#> 1 Alabama 2020-04-04 2020-04-30
#> 2 Alaska   2020-03-28 2020-04-24
#> 3 Arizona  2020-03-31 2020-05-15
#> 4 Arkansas None        None
#> 5 California 2020-03-19 2020-08-28
#> # i 1 more row

```

Both the mobility and lockdown data frames contain date columns. Right now, these columns in both data sets are of the class character, which we can see in the printed output above. We can use the `as.Date()` function to tell R to treat these columns as dates instead of characters. When using this function, we need to specify the date format as an argument so that R knows how to parse this text to a date. Our format is given as `%Y-%M-%D`, where the `%Y` stands for the full four-digit year, `%M` is a two-digit month (e.g. January is coded “01” vs “1”), and `%D` stands for the two-digit day (e.g. the third day is coded “03” vs “3”). Below, we convert the classes of these columns to ‘Date’.

```

mobility$date <- as.Date(mobility$date, formula = "%Y-%M-%D")
lockdowndates$Lockdown_Start <- as.Date(lockdowndates$Lockdown_Start, formula = "%Y-%M-%D")
lockdowndates$Lockdown_End <- as.Date(lockdowndates$Lockdown_End, formula = "%Y-%M-%D")
class(mobility$date)
#> [1] "Date"
class(lockdowndates$Lockdown_Start)
#> [1] "Date"
class(lockdowndates$Lockdown_End)
#> [1] "Date"

```

After coding these columns as dates, we can access information such as the day, month, year, or week from them. These functions are all available in the `lubridate` package, which is a package in the tidyverse that allows us to manipulate dates.

```
month(mobility$date[1])
#> [1] 3
week(mobility$date[1])
#> [1] 9
```

Next, we add a date column to `covidcases`. In this case, we need to use the week number to find the date. Luckily, we can add days, months, weeks, or years to dates in the `lubridate` package. January 1, 2020 was a Wednesday and is counted as the first week, so to find the corresponding Sunday for each week, we add the recorded week number minus one to December 29, 2019 (the last Sunday before 2020). We show a simple example of adding one week to this date below before doing this conversion for the entire column.

```
as.Date("2019-12-29")+weeks(1)
#> [1] "2020-01-05"

covidcases$date <- as.Date("2019-12-29")+weeks(covidcases$week-1)
head(covidcases)
#> # A tibble: 6 x 6
#> # Groups: state, county, week [6]
#>   state   county   week weekly_cases weekly_deaths date
#>   <chr>   <chr>    <dbl>      <int>        <int> <date>
#> 1 Alabama Autauga     12          3            0 2020-03-15
#> 2 Alabama Autauga     13          3            0 2020-03-22
#> 3 Alabama Autauga     14          2            1 2020-03-29
#> 4 Alabama Autauga     15         11            1 2020-04-05
#> 5 Alabama Autauga     16          5            1 2020-04-12
#> # i 1 more row
```

## 6.1 Tidy Data

The tidyverse is designed around interacting with **tidy data** with the premise that using data in a tidy format can streamline our analysis. Data is considered **tidy** if

1. Each variable is associated with a single column.
2. Each observation is associated with a single row.
3. Each value has its own cell.

Take a look at the sample data below which stores information about the maternal mortality rate for five countries over time (source: <https://ourworldindata.org/maternal-mortality>). This data is *not* tidy because the variable for maternity mortality rate is associated with multiple columns. Every row should correspond to one class observation.

```
mat_mort1 <- data.frame(country = c("Turkey", "United States", "Sweden", "Japan"),
                         y2002 = c(64, 9.9, 4.17, 7.8),
                         y2007 = c(21.9, 12.7, 1.86, 3.6),
                         y2012 = c(15.2, 16, 5.4, 4.8))

head(mat_mort1)
#>      country y2002 y2007 y2012
#> 1 Turkey    64.00 21.90 15.2
#> 2 United States 9.90 12.70 16.0
#> 3 Sweden    4.17  1.86  5.4
#> 4 Japan     7.80  3.60  4.8
```

However, we can make this data tidy by creating separate columns for country, year, and maternity mortality rate as we demonstrate below. Now every observation is associated with an individual row.

```
mat_mort2 <- data.frame(
  country = rep(c("Turkey", "United States", "Sweden", "Japan"), 3),
  year = c(rep(2002, 4), rep(2007, 4), rep(2012, 4)),
  mat_mort_rate = c(64.0, 9.9, 4.17, 7.8, 21.9, 12.7, 1.86, 3.6,
                   15.2, 16, 5.4, 4.8))

head(mat_mort2)
#>      country year mat_mort_rate
#> 1 Turkey 2002       64.00
#> 2 United States 2002      9.90
#> 3 Sweden 2002       4.17
#> 4 Japan 2002        7.80
#> 5 Turkey 2007      21.90
#> 6 United States 2007     12.70
```

## 6.2 Reshaping Data

The mobility and covid case data are both already in tidy form - each observation corresponds to a single row and every column is a single variable. We might consider whether the lockdown dates should be reformatted to be tidy. Another way to represent this data would be to have each observation be the start or end of a stay at home order.

To reshape our data, we use the `pivot_longer()` function to change the data from what is called **wide form** to what is called **long form**. This kind of pivot involves taking a subset of columns that we will *gather* into a single column while increasing the number of rows in the data set. Before pivoting, we have to think about which columns we are transforming. The image below shows a picture of some data on whether students have completed a physical, hearing, or eye exam. The data is presented in wide form on the left and long form on the right. To transform wide data to long data, we have identified a subset of columns `cols` that we want to transform (these `cols` are shown in light purple on the left). The long form contains a new column `names_to` that contains the exam type and `values_to` that contains a binary variable indicating whether or not each exam was completed.

In our case, we want to take the lockdown start and end columns and create two new columns: one column will indicate whether or not a date represents the start or end of a lockdown, and the other will contain the date itself. These are called the *key* and *value* columns, respectively. The key column will get its values from the names of the columns we are transforming (or the keys) whereas the value column will get its values from the entries in those columns (or the values).

The `pivot_longer()` function takes in a data table, the columns `cols` that we are pivoting to longer form, the column name `names_to` that will store the data from the previous column names, and the column name `values_to` for the column that will store the information from the columns gathered. In our case, we will name the first column `Lockdown_Event` since it will contain whether each date is the start or end of a lockdown, and we will name the second column `Date`. Take a look at the result below.

```
lockdown_long <- lockdowndates %>%
  pivot_longer(cols=c("Lockdown_Start", "Lockdown_End"),
               names_to="Lockdown_Event", values_to="Date") %>%
  mutate(Date = as.Date(Date, formula ="%Y-%M-%D"),
         Lockdown_Event = ifelse(Lockdown_Event=="Lockdown_Start",
                                 "Start", "End")) %>%
  na.omit()
head(lockdown_long)
#> # A tibble: 6 x 3
#>   State  Lockdown_Event Date
#>   <chr>  <chr>        <date>
#> 1 Alabama Start       2020-04-04
#> 2 Alabama End        2020-04-30
#> 3 Alaska  Start      2020-03-28
#> 4 Alaska  End        2020-04-24
#> 5 Arizona Start     2020-03-31
#> # i 1 more row
```

In R, we can also transform our data in the opposite direction (from long form to wide form instead of from wide form to long form) using the function `pivot_wider()`. This function again first takes in a data table but now we specify the arguments `names_from` and `values_from`. The former indicates the column that R should get the new column names from, and the latter indicates where the row values should be taken from. For example, in order to pivot our lockdown data back to wide form below, we specify that `names_from` is the lockdown event and `values_from` is the date itself. Now we are back to the same form as before!

```
lockdown_wide <- pivot_wider(lockdown_long, names_from=Lockdown_Event,
                               values_from=Date)
head(lockdown_wide)
#> # A tibble: 6 x 3
#>   State      Start      End
#>   <chr>     <date>    <date>
#> 1 Alabama  2020-04-04 2020-04-30
#> 2 Alaska   2020-03-28 2020-04-24
#> 3 Arizona  2020-03-31 2020-05-15
#> 4 California 2020-03-19 2020-08-28
#> 5 Colorado  2020-03-26 2020-04-26
#> # i 1 more row
```

Here's another example: suppose that I want to create a data frame where the columns correspond to the number of cases for each state in New England and the rows correspond to the numbered months. First, I need to filter my data to New England and then summarize my data to find the number of cases per month. I use the `month()` function to be able to group by month and state. Additionally, you can see that I add an `ungroup()` at the end. When we summarize on data grouped by more than one variable, the summarized output will still be grouped. In this case, the warning message states that the data is still grouped by state.

```
ne_cases <- covidcases %>%
  filter(state %in% c("Maine", "Vermont", "New Hampshire", "Connecticut", "Rhode Island",
                      "Massachusetts")) %>%
  mutate(month = month(date)) %>%
  group_by(state, month) %>%
  summarize(total_cases = sum(weekly_cases)) %>%
  ungroup()
head(ne_cases)
#> # A tibble: 6 x 3
#>   state      month total_cases
#>   <chr>     <dbl>     <int>
#> 1 Connecticut 3         6872
#> 2 Connecticut 4        18575
```

```

#> 3 Connecticut      5       11936
#> 4 Connecticut      6       2619
#> 5 Connecticut      7       2290
#> # i 1 more row

```

Now, I need to convert this data to wide format with a column for each state, so my `names_from` argument will be `state`. Further, I want each row to have the case values for each state, so my `values_from` argument will be `total_cases`. The format of this data may not be tidy, but it allows me to quickly compare cases across states.

```

pivot_wider(ne_cases, names_from=state, values_from=total_cases)
#> # A tibble: 7 x 7
#>   month Connecticut Maine Massachusetts `New Hampshire` `Rhode Island`
#>   <dbl>     <int> <int>     <int>           <int>           <int>
#> 1     3       6872    434     13118          651            827
#> 2     4      18575    725     47499         1649          6843
#> 3     5      11936   1575     28798         2179          14653
#> 4     6      2619    1185     5545          751            1426
#> 5     7      2290    1046     7621          827          65562
#> # i 2 more rows
#> # i 1 more variable: Vermont <int>

```

### 6.2.1 Practice Question

Create a similar data frame as we did above but this time using the `mobility` dataset. In other words, create a data frame where the columns correspond to the average mobility for each state in New England and the rows correspond to the numbered months. You should get a result that looks like this:

```
# Insert your solution here:
```

The pivots above were relatively simple in that there was only one set of values we were pivoting on (e.g. the lockdown date, covid cases). The `tidyR package` provides examples of more complex pivots that you might want to apply to your data. In the video below, we demonstrate a pivot longer when there is information in the column names, a pivot wider with multiple value columns, and a pivot longer with many variables in the columns.

### 6.2.2 Pivot Video

<https://www.youtube.com/embed/X4JnidcfUJw>

## 6.3 Merging Data with Joins

Above, we saw how to manipulate our current data into new formats. Now, we will see how we can combine multiple data sources. Merging two data frames is called *joining*, and the functions we will use to perform this joining depends on how we want to match values between the data frames. For example, below we join information about age and statin use from `table1` and `table2` matching by name.

```
table1 <- data.frame(age = c(14, 26, 32), name = c("Alice", "Bob", "Alice"))
table2 <- data.frame(name = c("Carol", "Bob"), statins = c(TRUE, FALSE))
full_join(table1, table2, by = "name")
#>   age  name statins
#> 1 14 Alice     NA
#> 2 26   Bob    FALSE
#> 3 32 Alice     NA
#> 4 NA Carol    TRUE
```

The list below shows an overview of the different possible joins, and the video talks through each join type. For each join type, we specify two tables, `table1` and `table2`, and the `by` argument, which specifies the columns used to match rows between tables.

### Types of Joins:

- `left_join(table1, table2, by)`: Joins each row of `table1` with all matches in `table2`.
- `right_join(table1, table2, by)`: Joins each row of `table2` with all matches in `table1` (the opposite of a left join)
- `inner_join(table1, table2, by)`: Looks for all matches between rows in `table1` and `table2`. Rows that do not find a match are dropped.
- `full_join(table1, table2, by)`: Keeps all rows from both tables and joins those that match. Rows that do not find a match will have NA values filled in.
- `semi_join(table1, table2, by)`: Keeps all rows in `table1` that have a match in `table2` but does not join to any information from `table2`.
- `anti_join(table1, table2, by)`: Keeps all rows in `table1` that *do not* have a match in `table2` but does not join to any information from `table2`. The opposite of a semi join.

### 6.3.1 Types of Joins Video

<https://www.youtube.com/embed/slazeLLQBoY>

We will first demonstrate a left join using the `left_join()` function. This function takes in two data tables (table1 and table 2) and the columns to match rows by. In a left join, for every row of table1, we look for all matching rows in table2 and add any columns not used to do the matching. Thus, every row in table1 corresponds to at least one entry in the resulting table but possibly more if there are multiple matches. Below, we use a left join to add the lockdown information to our `covidcases` data. In this case, the first table will be `covidcases` and we will match by `state`. Since the state column has a slightly different name in the two data frames (“state” in `covidcases` and “State” in `lockdowndates`), we specify that `state` is equivalent to `State` in the by argument.

```
covidcases_full <- left_join(covidcases, lockdowndates, by=c("state"="State"))
head(covidcases_full)
#> # A tibble: 6 x 8
#>   state    county    week weekly_cases weekly_deaths date
#>   <chr>    <chr>     <dbl>        <int>        <int> <date>
#> 1 Alabama  Autauga     12           3            0 2020-03-15
#> 2 Alabama  Autauga     13           3            0 2020-03-22
#> 3 Alabama  Autauga     14           2            1 2020-03-29
#> 4 Alabama  Autauga     15          11            1 2020-04-05
#> 5 Alabama  Autauga     16           5            1 2020-04-12
#> # i 1 more row
#> # i 2 more variables: Lockdown_Start <date>, Lockdown_End <date>
```

These two new columns will allow us to determine whether the start of each recorded week was during a lockdown. We use the `between` function to create a new column `lockdown` before dropping the two date columns. We can check that this column worked as expected by choosing a single county to look at.

```
covidcases_full <- covidcases_full %>%
  mutate(lockdown = between(date, Lockdown_Start, Lockdown_End)) %>%
  select(-c(Lockdown_Start, Lockdown_End))
covidcases_full %>%
  filter(state == "Alabama", county == "Jefferson", date <= as.Date("2020-05-10"))
#> # A tibble: 10 x 7
#>   state    county    week weekly_cases weekly_deaths date      lockdown
#>   <chr>    <chr>     <dbl>        <int>        <int> <date>    <lgl>
#> 1 Alabama  Jefferson     1             0            0 2020-03-15 FALSE
#> 2 Alabama  Jefferson     2             0            0 2020-03-22 FALSE
#> 3 Alabama  Jefferson     3             0            0 2020-03-29 FALSE
#> 4 Alabama  Jefferson     4             0            0 2020-04-05 FALSE
#> 5 Alabama  Jefferson     5             0            0 2020-04-12 FALSE
#> 6 Alabama  Jefferson     6             0            0 2020-04-19 FALSE
#> 7 Alabama  Jefferson     7             0            0 2020-05-06 FALSE
#> 8 Alabama  Jefferson     8             0            0 2020-05-13 FALSE
#> 9 Alabama  Jefferson     9             0            0 2020-05-20 FALSE
#> 10 Alabama Jefferson    10            0            0 2020-05-27 FALSE
```

```

#> 1 Alabama Jefferson    11      19      0 2020-03-08 FALSE
#> 2 Alabama Jefferson    12      66      0 2020-03-15 FALSE
#> 3 Alabama Jefferson    13     153      0 2020-03-22 FALSE
#> 4 Alabama Jefferson    14     156      8 2020-03-29 FALSE
#> 5 Alabama Jefferson    15     128      2 2020-04-05 TRUE
#> # i 5 more rows

```

We now want to add in the mobility data. In the join above, we wanted to keep any observation in `covidcases` regardless if it was in the `lockdowndates` data frame. Therefore, we used a left join. In this case, we will only want to keep observations that have mobility date for that state on each date. This indicates that we want to use an *inner join*. The function `inner_join()` takes in two data tables (table1 and table2) and the columns to match rows by. The function only keeps rows in table1 that match to a row in table2. Again, those columns in table2 not used to match with table1 are added to the resulting outcome. In this case, we match by both state and date.

```

covidcases_full <- inner_join(covidcases_full, mobility, by = c("state", "date")) %>%
  select(-c(samples, m50_index))
head(covidcases_full)
#> # A tibble: 6 x 8
#>   state   county   week weekly_cases weekly_deaths date      lockdown
#>   <chr>   <chr>   <dbl>       <int>        <int> <date>      <lgl>
#> 1 Alabama Autauga    12          3           0 2020-03-15 FALSE
#> 2 Alabama Autauga    13          3           0 2020-03-22 FALSE
#> 3 Alabama Autauga    14          2           1 2020-03-29 FALSE
#> 4 Alabama Autauga    15          11          1 2020-04-05 TRUE
#> 5 Alabama Autauga    16          5           1 2020-04-12 TRUE
#> # i 1 more row
#> # i 1 more variable: m50 <dbl>

```

### 6.3.2 Practice Question

Look at the two data frames, `df_A` and `df_B`, created in the below code. What kind of join would produce the following data frame? Perform this join yourself.

```

df_A <- data.frame(patient_id = c(12, 9, 12, 8, 14, 8),
                    visit_num = c(1, 1, 2, 1, 1, 2),
                    temp = c(97.5, 96, 98, 99, 102, 98.6),
                    systolic_bp = c(120, 138, 113, 182, 132, 146))

```

```

df_A
#>   patient_id visit_num  temp systolic_bp
#> 1        12       1  97.5      120
#> 2         9       1  96.0      138
#> 3        12       2  98.0      113
#> 4         8       1  99.0      182
#> 5        14       1 102.0      132
#> 6         8       2  98.6      146
df_B <- data.frame(patient_id = c(12, 12, 12, 8, 8, 8, 14, 14),
                     visit_num = c(1, 2, 3, 1, 2, 3, 1, 2),
                     digit_span = c(3, 5, 7, 7, 9, 5, 8, 7))
df_B
#>   patient_id visit_num digit_span
#> 1        12       1          3
#> 2        12       2          5
#> 3        12       3          7
#> 4         8       1          7
#> 5         8       2          9
#> 6         8       3          5
#> 7        14       1          8
#> 8        14       2          7

# Insert your solution here:

```

## 6.4 Exercises

- Take a look at the code below - what is wrong with it? Hint: think about what causes the warning message.

```

visit_info <- data.frame(
  name.f = c("Phillip", "Phillip", "Phillip", "Jessica", "Jessica"),
  name.l = c("Johnson", "Johnson", "Richards", "Smith", "Abrams"),
  measure = c("height", "age", "age", "age", "height"),
  measurement = c(45, 186, 50, 37, 156)
)

contact_info <- data.frame(
  first_name = c("Phillip", "Phillip", "Jessica", "Margaret"),
  last_name = c("Richards", "Johnson", "Smith", "Reynolds"),

```

```

email = c("pr@aol.com", "phillipj@gmail.com", "jesssmith@brown.edu", "marg@hotmail.com")
)

left_join(visit_info, contact_info, by = c("name.f" = "first_name"))
#> Warning in left_join(visit_info, contact_info, by = c(name.f = "first_name")): Detected
#> i Row 1 of `x` matches multiple rows in `y`.
#> i Row 1 of `y` matches multiple rows in `x`.
#> i If a many-to-many relationship is expected, set `relationship =
#>   "many-to-many"` to silence this warning.
#>   name.f   name.l measure measurement last_name           email
#> 1 Phillip  Johnson  height        45  Richards      pr@aol.com
#> 2 Phillip  Johnson  height        45  Johnson    phillipj@gmail.com
#> 3 Phillip  Johnson   age       186  Richards      pr@aol.com
#> 4 Phillip  Johnson   age       186  Johnson    phillipj@gmail.com
#> 5 Phillip Richards   age        50  Richards      pr@aol.com
#> 6 Phillip Richards   age        50  Johnson    phillipj@gmail.com
#> 7 Jessica  Smith    age        37   Smith    jesssmith@brown.edu
#> 8 Jessica  Abrams   height      156   Smith    jesssmith@brown.edu

```

2. First, use the `covidcases` data to create a new data frame called `sub_cases` containing the total number of cases by month for the states of California, Michigan, Connecticut, Rhode Island, Ohio, New York, and Massachusetts. Then, manipulate the `mobility` data to calculate the average `m50` mobility measure for each month. Finally, merge these two data sets using an appropriate joining function.
3. Convert the `sub_cases` data frame from the previous exercise to wide format so that each row displays the cases in each state for a single month. Then, add on the average `m50` overall for each month as an additional column using a join function.

# 7 Visualization with ggplot2

`ggplot2` is another useful package in the tidyverse that allows statisticians to use visualizations to communicate key findings and results in a compelling format. We will first learn about the three main components in a `ggplot` object and then expand on that format by learning more about the different layers we can use to create various plots. As with the tidyverse functions, there are quite a few functions to cover, and the functions build on each other.

The three packages we will use in this chapter are `tidyverse`, `HDSinRdata`, and `patchwork`, the last of which is a nice package for combining multiple plots together into a single figure. We will use the data from the Pittsburgh pain clinic introduced in Chapter 3 to create our visuals. You can refresh your memory about this data by reading the data documentation. For the purposes of this chapter, we take a sample of 5,000 patients that are complete cases at baseline to reduce the computation time to display each plot. You can ignore how the code used to find this sample works.

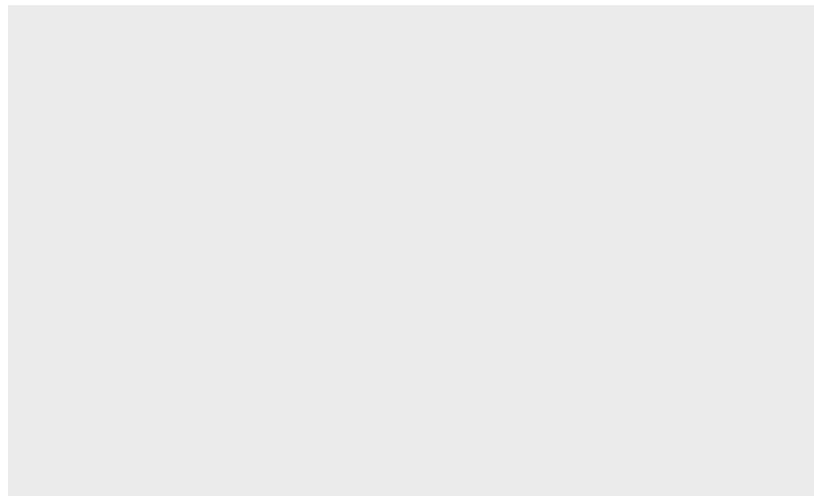
```
suppressPackageStartupMessages(library(tidyverse))
suppressPackageStartupMessages(library(HDSinRdata))
suppressPackageStartupMessages(library(patchwork))
data(pain)

# sampling data
set.seed(5)
pain_df <- pain[complete.cases(subset(pain,
                                         select=-c(PAIN_INTENSITY_AVERAGE.FOLLOW_UP))),]
pain_df <- pain_df[sample(1:nrow(pain_df), 5000, replace=FALSE),]
```

## 7.1 Intro to ggplot

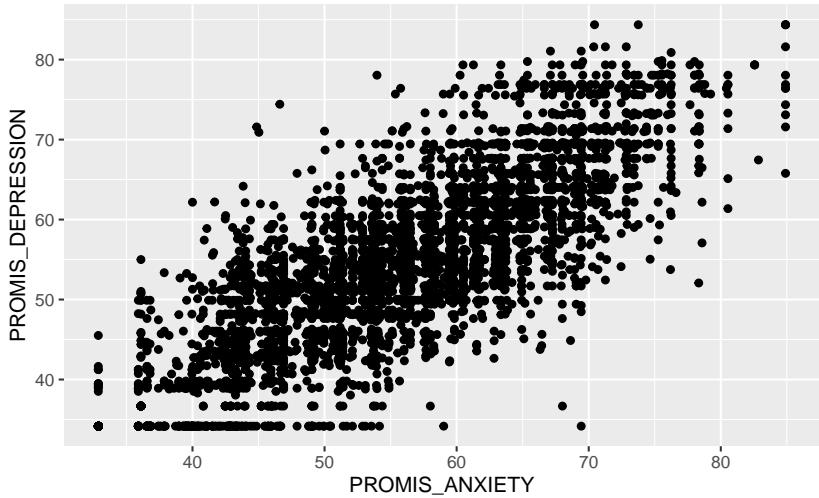
We'll begin by demonstrating how to create a scatter plot in `ggplot2` to introduce the three key elements of a `ggplot2` object. Specifically, we will create a scatter plot of a patient's depression vs. anxiety score. To start a graph, we can use the `ggplot()` function to create a `ggplot` object as below. Note that this brings up a gray box - this will be the base that we will build up from.

```
ggplot()
```



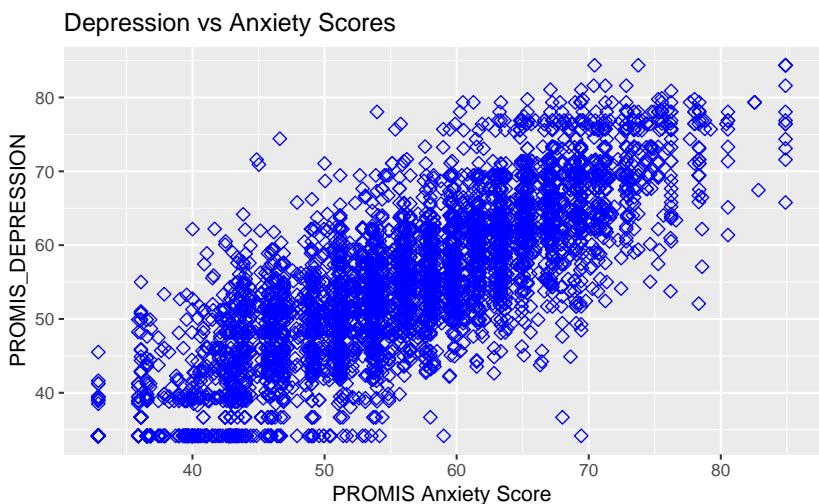
Now we can start adding layers to our `ggplot` object. One type of layer is a **geom**, which creates a geometric object. Below, we use the `geom_point()` function to add a scatter plot layer. For this function, we first need to specify which data we want to use, and then we need to tell R how to use that data to create the scatter plot using the `aes()` function, which creates an **aesthetic**. For a scatter plot, we need to at least specify the x-axis and y-axis in the aesthetic. Both the data and the aesthetic can either be specified in our initial `ggplot()` function, which will pass this information to all future layers, or in the `geom_point()` function itself. Below, we specify the aesthetic in the geom function but also include two alternative ways to code the same image that are commented out. The resulting plot shows a fairly linear relationship between anxiety and depression.

```
ggplot(pain_df) + geom_point(aes(x=PROMIS_ANXIETY, y = PROMIS_DEPRESSION))  
# ggplot(pain_df, aes(x=PROMIS_ANXIETY, y = PROMIS_DEPRESSION)) + geom_point()  
# ggplot() + geom_point(data = pain_df, aes(x=PROMIS_ANXIETY, y = PROMIS_DEPRESSION))
```



If we want to improve our plot, we may want to add different labels and a title. To do so, we use the `labs()` function to add a layer in which we can specify all labels. Additionally, I have passed more information to the geometry layer by changing the `color`, `size`, and `shape` of the points. These things are specified outside of the `aes()` function since they do not come from the data - every point has the same color, size, and shape in this example.

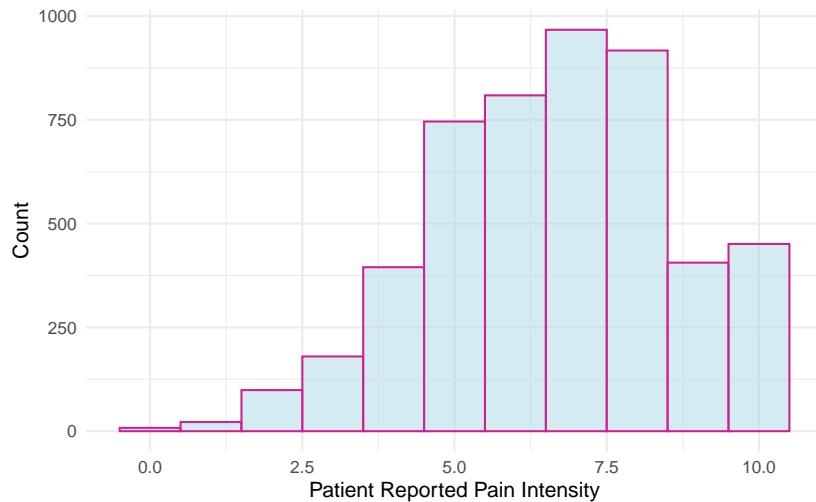
```
ggplot(pain_df)+  
  geom_point(aes(x=PROMIS_ANXIETY, y = PROMIS_DEPRESSION),  
             color="blue", size=2, shape=5) +  
  labs(x="PROMIS Anxiety Score", ylab="PROMIS Depression Score",  
       title = "Depression vs Anxiety Scores")
```



Let's create another example. This time, I will create a histogram for initial recorded pain level. To find the corresponding geom for the type of plot we'd like to make, we can use the [data visualization cheat sheet from Posit](#). The first page lists all the geom options available along with what aesthetics we can set for each option. For example, here we are interested in plotting the distribution of one continuous variable, and under the `geom_histogram()` function we can see that we can specify `x` (the variable whose distribution we want to plot) as well as `binwidth`, `y`, `alpha`, `color`, `fill`, `linetype`, `size`, and `weight`. By default, the `y` value in a histogram is the count for each bin.

In the code below, you can see that we updated the color (`color`), fill (`fill`), and opacity (`alpha`) of our histogram bars and updated the number of bins to be 11 (to account for the possible values 0-10). Additionally, we used the `theme_minimal()` function to change the background colors used. You can find the available themes on the second page of the cheat sheet. Try changing the theme of the above plot to `theme_bw()`.

```
ggplot(pain_df)+  
  geom_histogram(aes(x=PAIN_INTENSITY_AVERAGE), color="violetred",  
                 fill="lightblue", alpha=0.5, bins = 11) +  
  labs(x="Patient Reported Pain Intensity", y="Count") +  
  theme_minimal()
```



### 7.1.1 Practice Question

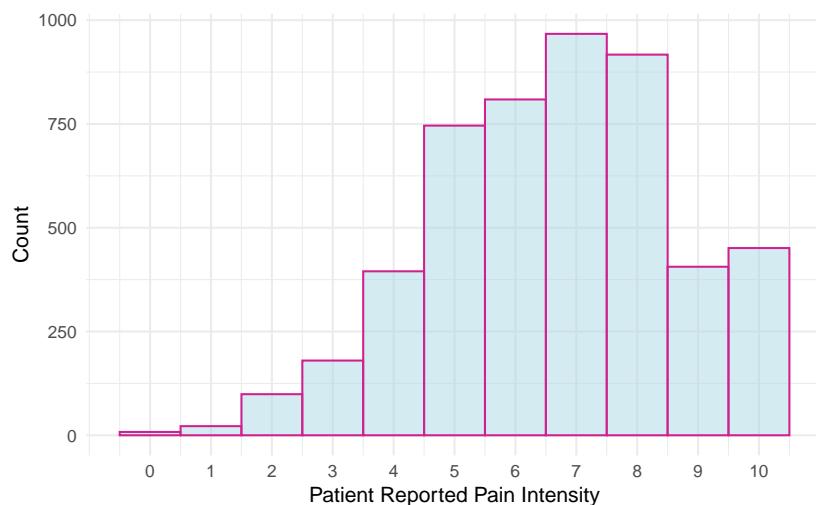
Recreate the following plot.

```
# Insert your solution here:
```

## 7.2 Adjusting the Axes and Aesthetics

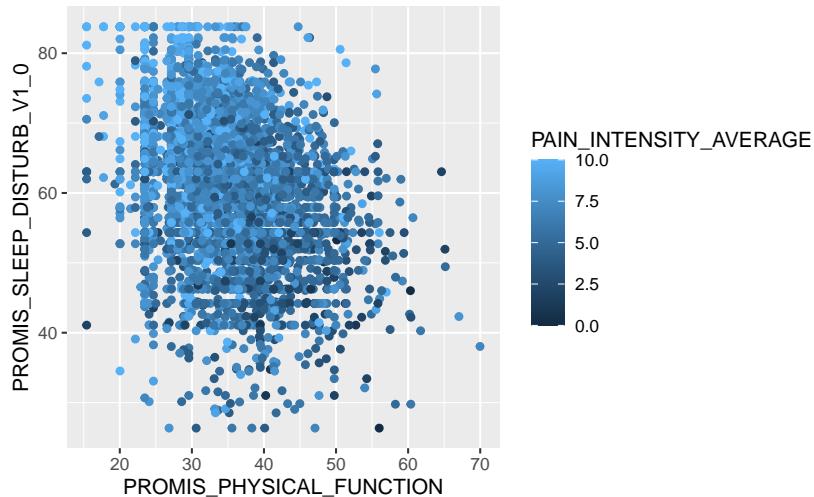
We can further control how each part specified in the aesthetic is displayed using **scale** functions. For example, suppose that I wanted to update the plot above. In particular, I first want to update the x-axis to display all of the values 0 to 10 instead of 0, 2.5, 5, etc.. To update the x-axis, I need to find the corresponding scale function for x with continuous values. This function is **scale\_x\_continuous()**, which allows me to specify limits (**limits**), breaks (**breaks**), and labels (**labels**). The scale functions can be found on the second sheet of the cheat sheet. In this case, I just want to update the breaks to be all integer values from 0 to 10.

```
ggplot(pain_df)+  
  geom_histogram(aes(x=PAIN_INTENSITY_AVERAGE), color="violetred",  
                 fill="lightblue", alpha=0.5, bins = 11) +  
  labs(x="Patient Reported Pain Intensity", y="Count") +  
  scale_x_continuous(breaks=0:10) +  
  theme_minimal()
```



Now, let's take a more complex example. The plot below shows each patient's reported sleep disturbance vs. physical function and colors each point by their reported pain intensity. Since some points might overlap in values, we added **position="jitter"** to the **geom\_point()** function to jitter the points, which corresponds to adding some random noise to each point's position. As it stands, this plot is difficult to read. For example, the color of pain intensity makes it hard to see how pain changes, and the legend title needs to be simpler.

```
ggplot(pain_df) +
  geom_point(aes(x=PROMIS_PHYSICAL_FUNCTION, y=PROMIS_SLEEP_DISTURB_V1_0,
                 color=PAIN_INTENSITY_AVERAGE), position="jitter")
```



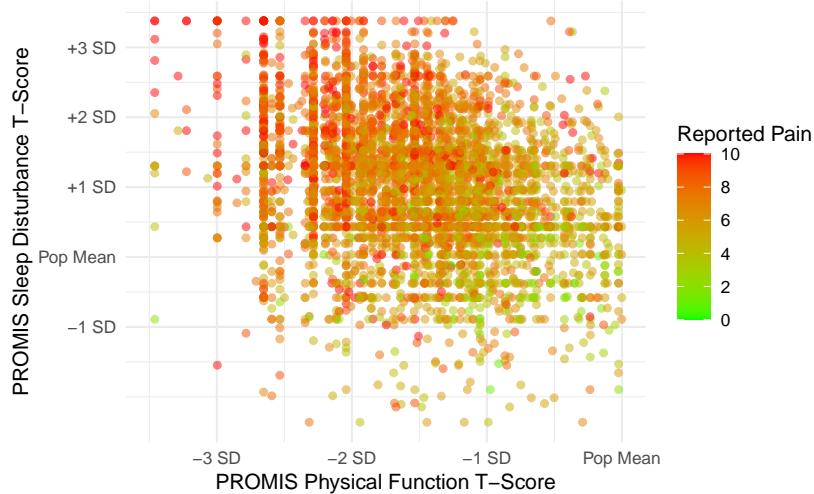
Suppose that we wanted to visualize the pain intensity and sleep disturbance for patients with below-average physical function. Note that both sleep disturbance and physical function are reported as T-Scores, meaning that the raw scores have been converted to a standardized score with mean 50 and standard deviation 10 within the population. We can use the scale functions to update our axes and labels to reflect this information. As before, we need to use the `scale_x_continuous()` function to update the x-axis for a continuous variable. In this case, we update the limits (to restrict to below average physical function), breaks, and labels. We similarly update the y-axis.

Lastly, suppose we want to update the color aesthetic. As before, this aesthetic corresponds to a continuous variable. The cheat sheet provides several possible scale functions depending on how we want to specify the color gradient. We choose the `scale_color_gradient()` function, since this allows us to specify the low and high end colors. We can also specify the breaks for the legend values similar to how we specified the breaks for the x and y axes. The argument `name` also allows us to rename this legend. The palette then converts this to a continuous color gradient. Note that in contrast to the `scale_color_gradient()` function that we chose to use for this example, the functions `scale_color_gradient2()` and `scale_color_gradientn()` allow you to specify more color points in the gradient rather than just the two extreme colors.

We can observe that decreased physical function is associated with higher sleep disturbance and that those with worse physical function and worse sleep disturbance tend to have higher reported pain. Note that this time we receive a warning message, which is because our axis limits

have cut off some points. To avoid this message, we could use the function `coord_cartesian()` to specify our limits which clips the values rather than removing points outside the limits.

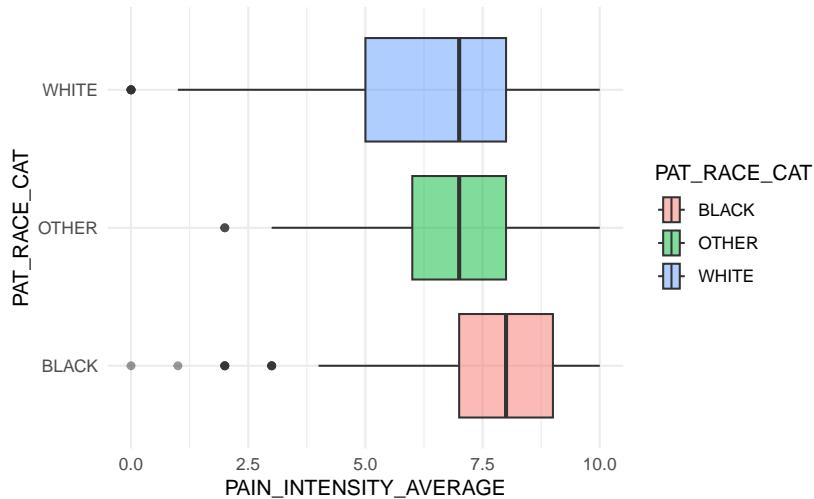
```
ggplot(pain_df)+  
  geom_point(aes(x=PROMIS_PHYSICAL_FUNCTION, y=PROMIS_SLEEP_DISTURB_V1_0,  
                 color=PAIN_INTENSITY_AVERAGE), position="jitter", alpha=0.5) +  
  scale_x_continuous(limits=c(15,50), breaks = c(20, 30, 40, 50),  
                     labels = c("-3 SD", "-2 SD", "-1 SD", "Pop Mean")) +  
  scale_y_continuous(breaks = c(40, 50, 60, 70, 80),  
                     labels = c("-1 SD", "Pop Mean", "+1 SD", "+2 SD", "+3 SD")) +  
  scale_color_gradient(breaks= seq(0,10,2), low="green", high="red", "Reported Pain") +  
  labs(x="PROMIS Physical Function T-Score", y = "PROMIS Sleep Disturbance T-Score") +  
  theme_minimal()  
#> Warning: Removed 121 rows containing missing values (`geom_point()`).
```



We now demonstrate these scale functions for discrete variables. In the example below, we first create a new race variable that has only three categories since other groups have limited observations. We then create a box plot for pain intensity by race. There are two discrete aesthetics here: color and the y-axis. This plot shows a higher median pain for black patients compared to other races.

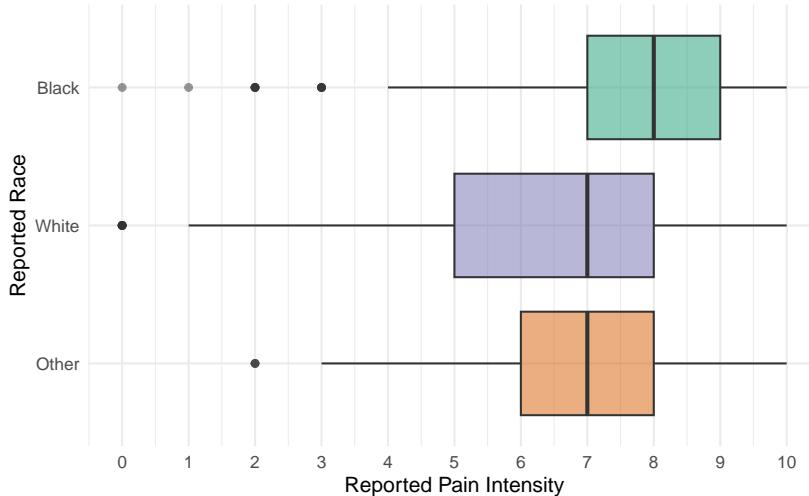
```
pain_df$PAT_RACE_CAT <- ifelse(pain_df$PAT_RACE %in% c("BLACK", "WHITE"),  
                                 pain_df$PAT_RACE, "OTHER")  
pain_df$PAT_RACE_CAT <- as.factor(pain_df$PAT_RACE_CAT)
```

```
ggplot(pain_df) +
  geom_boxplot(aes(y=PAT_RACE_CAT, x=PAIN_INTENSITY_AVERAGE,
                    fill=PAT_RACE_CAT), alpha=0.5) +
  theme_minimal()
```



The function `scale_y_discrete()` is the scale function that corresponds to a discrete y-axis. In this case, we want to update the order and labels of this y-axis. To update the order, we can either refactor the variable using `factor()` prior to plotting or update the `limits` argument of the scale function. The function `scale_fill_brewer()` is a scale function to control the color palette of a discrete variable used for the fill aesthetic. We use this function to specify the `color palette (palette)` and to specify that that we do not want a legend (`guide`). Since we do not have a legend, we do not update the values and labels in this function.

```
ggplot(pain_df) +
  geom_boxplot(aes(y=PAT_RACE_CAT, x=PAIN_INTENSITY_AVERAGE,
                    fill=PAT_RACE_CAT), alpha=0.5) +
  scale_x_continuous(breaks=c(0:10)) +
  scale_y_discrete(limits=c("OTHER", "WHITE", "BLACK"),
                   labels=c("Other", "White", "Black")) +
  scale_fill_brewer(palette="Dark2", guide="none") +
  labs(x="Reported Pain Intensity", y="Reported Race") +
  theme_minimal()
```

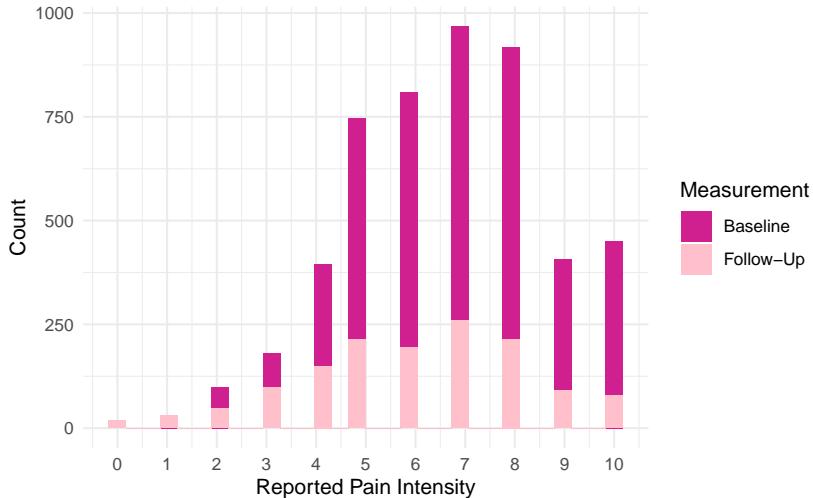


Here is one more example of how you can use the scale functions - take a look at the code below. We used two `geom_histogram()` calls, or layers, to plot a histogram of pain at baseline and at follow-up. This allows us to visualize that pain at follow-up tends to be lower than at baseline.

We also specify the fill to be by “Baseline” and “Follow-up” within the aesthetic, even though this isn’t a column in the data: this is a sort of manual way to color the bars. We use the `scale_fill_manual()` function to then specify the colors we want to use for these two categories using the `values` argument. We received three warnings when creating this plot! This is because we have many NA values for follow-up and because we did not specify the bin size for either histogram. C'est la vie.

```
ggplot(pain_df) +
  geom_histogram(aes(x=PAIN_INTENSITY_AVERAGE, fill="Baseline")) +
  geom_histogram(aes(x=PAIN_INTENSITY_AVERAGE.FOLLOW_UP, fill="Follow-Up")) +
  scale_x_continuous(breaks=c(0:10)) +
  scale_fill_manual(values=c("violetred", "pink"), name="Measurement") +
  labs(x="Reported Pain Intensity", y = "Count") +
  theme_minimal()

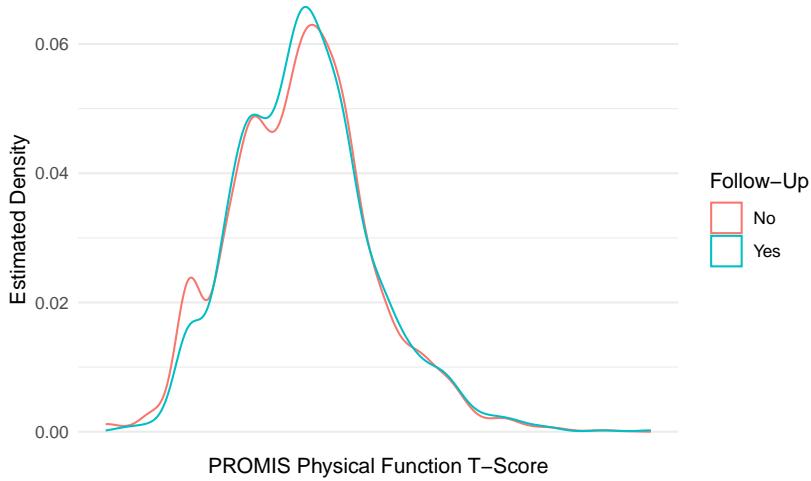
#> `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
#> `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
#> Warning: Removed 3604 rows containing non-finite values (`stat_bin()`).
```



### 7.3 Adding Groups

In the example above, we created two histograms using two calls to the `geom_histogram()` function, but there is another way to create multiple layers like this when you have a variable that you want to separate the geom layer on. For example, suppose we want to visualize the distribution of physical function by whether someone has follow-up information. Below we create the variable `HAS_FOLLOW_UP` before using it in our aesthetic for `geom_density()` as both the color and group. In fact, we do not have to add the `group` argument because as soon as we specify to R that we want to color the density plots by this variable, R will create the grouping. Finally, we update the legend for this grouping using the `scale_color_discrete()` function, since the discrete variable `HAS_FOLLOW_UP` specifies the color.

```
pain_df$HAS_FOLLOW_UP <- !is.na(pain_df$PAIN_INTENSITY_AVERAGE.FOLLOW_UP)
ggplot(pain_df) +
  geom_density(aes(x=PROMIS_PHYSICAL_FUNCTION, group=HAS_FOLLOW_UP,
                   color=HAS_FOLLOW_UP)) +
  scale_x_continuous(breaks=c(0:10)) +
  scale_color_discrete(name="Follow-Up", labels = c("No", "Yes")) +
  labs(x="PROMIS Physical Function T-Score", y="Estimated Density") +
  theme_minimal()
```

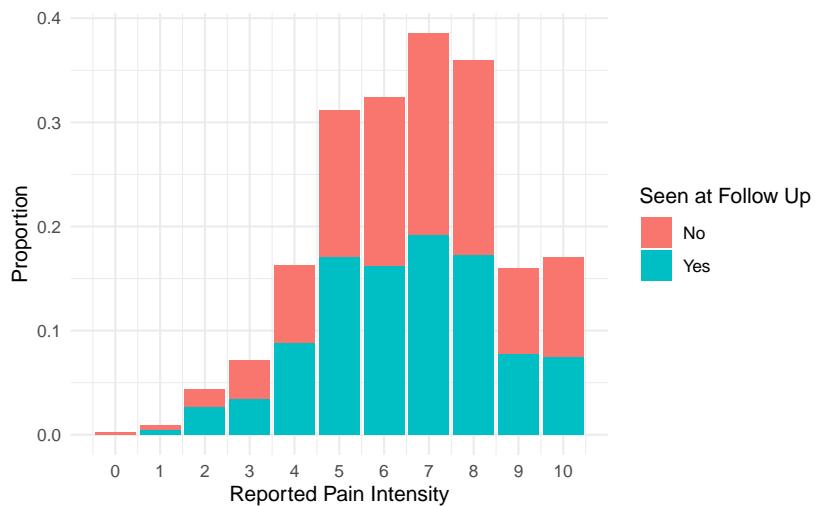


Let's try another example. Suppose that we want to find the distribution of initial overall pain by those that do and do not have follow up. In this case, we want to plot the proportion of each pain score for each group rather than comparing counts. We first need to find these proportions, which we do by grouping and summarizing over our data.

```
pain_df_grp <- pain_df %>%
  group_by(HAS_FOLLOW_UP, PAIN_INTENSITY_AVERAGE) %>%
  summarize(tot = n()) %>%
  mutate(prop = tot/sum(tot)) %>%
  ungroup()
head(pain_df_grp)
#> # A tibble: 6 x 4
#>   HAS_FOLLOW_UP PAIN_INTENSITY_AVERAGE     tot     prop
#>   <lgl>           <dbl> <int>    <dbl>
#> 1 FALSE              0      8  0.00222
#> 2 FALSE              1     16  0.00444
#> 3 FALSE              2     62  0.0172 
#> 4 FALSE              3    132  0.0366
#> 5 FALSE              4    273  0.0757
#> # i 1 more row
```

We can now use the `geom_col()` function to create a bar plot of these proportions. By default, this function will stack the bars on top of each other when there is grouping. Try adding `position="dodge"` to the `geom_col()` function to place the bars side by side instead of on top of each other.

```
ggplot(pain_df_grp) +
  geom_col(aes(x=PAIN_INTENSITY_AVERAGE, y=prop, fill=HAS_FOLLOW_UP)) +
  scale_x_continuous(breaks=c(0:10)) +
  scale_fill_discrete(name="Seen at Follow Up", labels=c("No", "Yes")) +
  labs(x="Reported Pain Intensity", y = "Proportion") +
  theme_minimal()
```



### 7.3.1 Practice Question

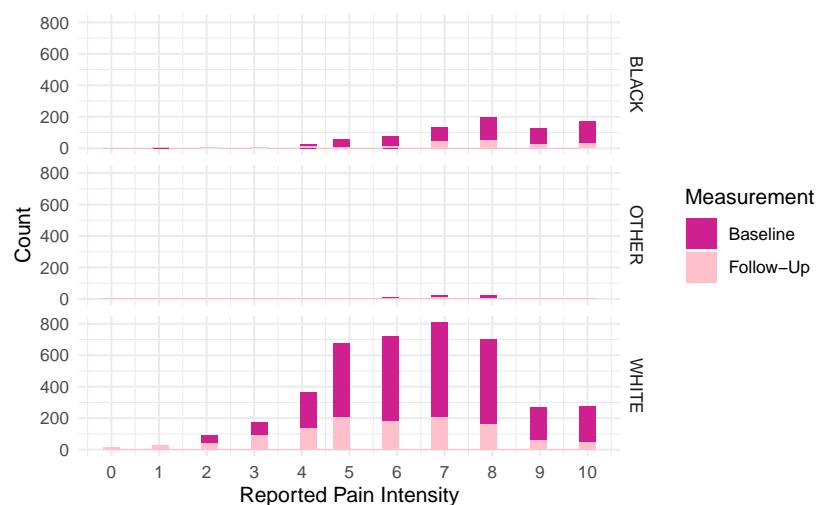
Recreate the following plot.

```
# Insert your solution here:
```

Another way to visualize data by group is to add a facet wrap to your ggplot object. Facets divide a plot into subplots based on one or more discrete variable values. We can either arrange these plots as a grid where the rows and/or columns correspond to the variables we are grouping by using `facet_grid()` and specifying the column and row variables using the `col` and `row` arguments respectively. Or we can wrap the plots into a rectangular format using `facet_wrap()` and specifying the columns using the `facet` argument. Below, we take one of our previous plots and add a facet grid where the columns of the grid are given by racial group. If we had set `row=vars(PAT_RACE_CAT)`, then this would stack the plots vertically. Note that we have to specify the variables inside the `vars()` function.

```
ggplot(pain_df) +
  geom_histogram(aes(x=PAIN_INTENSITY_AVERAGE, fill="Baseline")) +
```

```
geom_histogram(aes(x=PAIN_INTENSITY_AVERAGE.FOLLOW_UP, fill="Follow-Up")) +  
  scale_x_continuous(breaks=c(0:10)) +  
  scale_fill_manual(values=c("violetred", "pink"), name="Measurement") +  
  labs(x="Reported Pain Intensity", y = "Count") +  
  facet_grid(row=vars(PAT_RACE_CAT))+  
  theme_minimal()  
#> `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.  
#> `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.  
#> Warning: Removed 3604 rows containing non-finite values (`stat_bin()`).
```



## 7.4 Extra Options

To create our final plot, we will demonstrate some extra features we haven't covered so far. To create this plot, we first find the number of participants who selected each body region as well as the average pain intensity for those patients. We also classify each body part region into larger groups.

```

pain_body_map <- data.frame(part = names(pain_df)[2:75])
pain_body_map$num_patients <- colSums(pain_df[,2:75])
pain_body_map$perc_patients <- pain_body_map$num_patients/nrow(pain_df)
pain_body_map$avg_pain <- colSums(pain_df[,2:75] * pain_df$PAIN_INTENSITY_AVERAGE)/pain_df$avg_pain
pain_body_map <- pain_body_map %>%
  mutate( region = case_when(
    part %in% c("X208", "X209", "X218", "X219", "X212", "X213") ~ "Back",
    part %in% c("X210", "X211", "X214", "X215", "X216", "X217") ~ "Front"
  )
)

```

```

part %in% c("X105", "X106", "X205", "X206") ~ "Neck",
part %in% c("X107", "X110", "X207", "X210") ~ "Shoulders",
part %in% c("X108", "X109", "X112", "X113") ~ "Chest/Abs",
part %in% c("X126", "X127", "X228", "X229",
           "X131", "X132", "X233", "X234") ~ "Legs",
part %in% c("X111", "X114", "X211", "X214", "X115", "X116",
           "X117", "X118", "X217", "X220") ~ "Arms",
part %in% c("X119", "X124", "X221", "X226", "X125", "X128",
           "X227", "X230") ~ "Wrists/Hands",
part %in% c("X215", "X216") ~ "Elbows",
part %in% c("X135", "X136", "X237", "X238", "X133", "X134",
           "X235", "X236") ~ "Feet/Ankles",
part %in% c("X129", "X130", "X231", "X232") ~ "Knees",
part %in% c("X101", "X102", "X103", "X104", "X201", "X203",
           "X202", "X204") ~ "Head",
part %in% c("X120", "X121", "X122", "X123", "X222", "X223",
           "X224", "X225") ~ "Hips"))

```

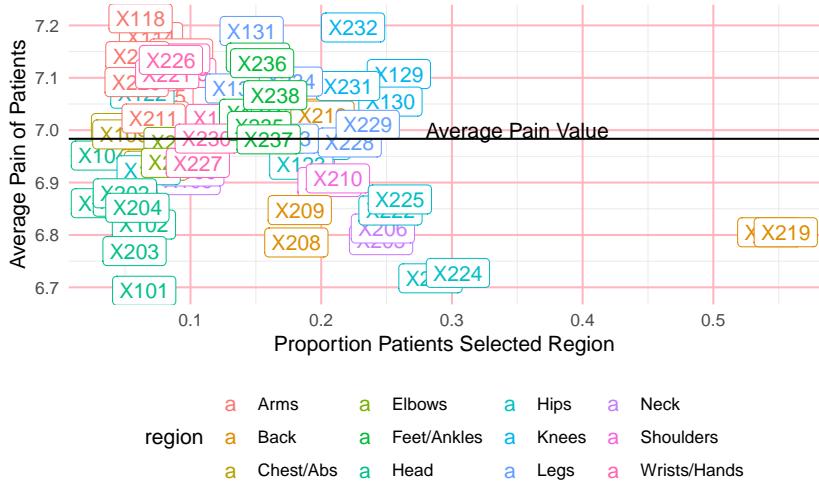
	part	num_patients	perc_patients	avg_pain	region
#>	X101	323	0.0646	6.69	Head
#>	X102	322	0.0644	6.82	Head
#>	X103	165	0.0330	6.86	Head
#>	X104	165	0.0330	6.95	Head
#>	X105	493	0.0986	6.90	Neck
#>	X106	507	0.1014	6.92	Neck

Within the theme we've chosen, we are able to update any of the [theme options](#). Below we use the `theme()` function to update the legend position to the bottom and the grid lines to light pink. Additionally, we add a horizontal line using the `geom_hline()` function (`geom_vline()` and `geom_abline()` can add vertical or diagonal lines respectively) and add a text annotation using the `annotate()` function. The resulting plot below shows the average pain value for each body part as well as the proportion of patients who categorized it as being painful.

```

ggplot(pain_body_map) +
  geom_label(aes(x=perc_patients, y=avg_pain, label=part, color=region)) +
  geom_hline(yintercept=mean(pain_body_map$avg_pain)) +
  annotate(geom="text", label="Average Pain Value", x=0.35, y=7.0) +
  labs(x="Proportion Patients Selected Region", y="Average Pain of Patients") +
  theme_minimal()+
  theme(legend.position="bottom", panel.grid.major = element_line(colour = "lightpink"))

```



So far we have not saved any of our figures as objects. Below, I create two plots and save them as objects named p1 and p2. If we want to save these plots, we can use the `ggsave()` function, which saves the last plot generated under the file name provided. Additionally, I can use the `patchwork` package to incorporate multiple plots together. A + between plots puts them side by side whereas / stacks them.

```
p1 <- ggplot(pain_body_map) +
  geom_label(aes(x=perc_patients, y=avg_pain, label=part, color=region)) +
  geom_hline(yintercept=mean(pain_body_map$avg_pain)) +
  annotate(geom="text", label="Average Pain Value", x=0.35, y=7.0) +
  labs(x="Proportion Patients Selected Region", y="Average Pain of Patients") +
  theme_minimal()+
  theme(legend.position="bottom", panel.grid.major = element_line(colour = "lightpink"))

p2 <- ggplot(pain_body_map) +
  geom_histogram(aes(x=perc_patients), color="violetred", fill="lightpink") +
  labs(x="Proportion of Patients Selected Region", y="Count") +
  theme_minimal()+
  theme(panel.grid.major = element_line(colour = "lightpink"))

p1/p2
#> `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



```
ggsave("images/myplot.png")
#> Saving 6 x 3.71 in image
#> `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

## 7.5 Recap Video

<https://www.youtube.com/embed/0atAfk6Yk10>

## 7.6 Exercises

For this chapter's exercises, use the `covidcases` data set that we first introduced in [Chapter 5](#) to recreate the plots below. These are complex plots, so try to build them up one step at a time and just try to get as close as possible to the given examples.

1. Replicate the plot below, which shows the weekly Covid-19 cases by state in 2020 - the black vertical line signifies the week of May 28th, 2020, which is when US cases passed the 100,000 mark (this date was taken from this [timeline](#), and NA values are displayed as white squares). Hint: set negative weekly case counts to be NA and color the squares with a log 10 transformation.
2. Replicate the plot below, which is a stacked area chart for the total deaths from Covid-19 in the states with the top ten total death counts overall.

## **Part III**

# **Distributions and Hypothesis Testing**

# 8 Probability Distributions in R

In this chapter, we will cover how to generate random samples in R from known probability distributions and empirical distributions. All of the common probability distributions have a set of four functions in base R that can be used to generate random samples and to calculate the corresponding density, quantile, and cumulative functions that correspond to that distribution.

```
suppressPackageStartupMessages(library(tidyverse))
suppressPackageStartupMessages(library(HDSinRdata))
data(NHANESsample)
```

Below, we demonstrate an example of drawing random samples. Anytime we do something in R in which the outcome has some randomness, we are using R's random number generator under the hood. This means that the results will change every time we run our code. In order to make sure our code is replicable, we have to set a random seed, which makes the results the same every time. The `set.seed()` function takes in a numeric seed value. You can use any number as the seed. Below, we first sample a random value from the numbers 1 to 10 without setting a seed. Note that every time you run this code chunk, the output can change. However, in the second code chunk we set a seed, which means that the result will always be the same (in this case, it's equal to 2).

```
sample(1:10, 1)
#> [1] 7

set.seed(5)
sample(1:10, 1)
#> [1] 2
```

## 8.1 Probability Distributions in R

All of the common discrete (e.g. Bernoulli, binomial) and continuous (e.g. normal, uniform, exponential, poisson) probability distributions have corresponding functions in R. For each of these distributions, there are four available functions:

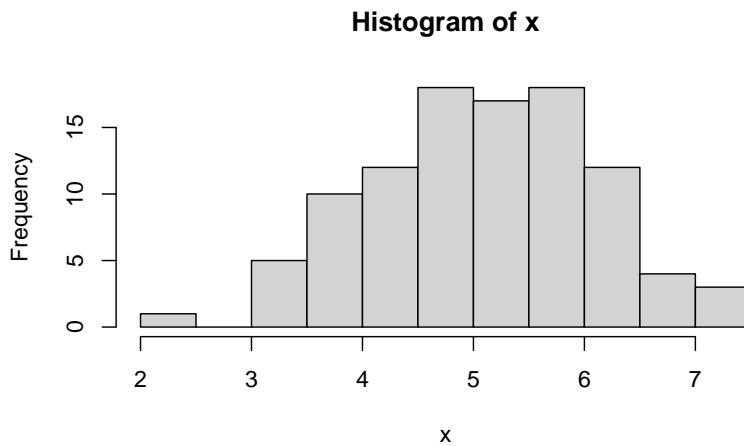
- `r[dist]()`: generates random samples from the given distribution (e.g. `rnorm()`, `runif()`)
- `d[dist]()`: density function for the distribution (e.g. `dnorm()`, `dunif()`)
- `p[dist]()`: cumulative distribution function for the distribution (e.g. `pnorm()`, `punif()`)
- `q[dist]()`: quantile function for the distribution (e.g. `qnorm()`, `qunif()`)

Let's see how these work in practice, using the normal and binomial distributions as examples.

### 8.1.1 Random Samples

The code below generates a sample of 100 random numbers following a normal distribution with mean 5 and standard deviation 1. As you can see, the function takes in `n` (the number of observations), `mean` (the mean with default value 0), and `sd` (the standard deviation with default value 1). A histogram plot (using the built-in `hist` function) shows that the generated values look roughly normally distributed.

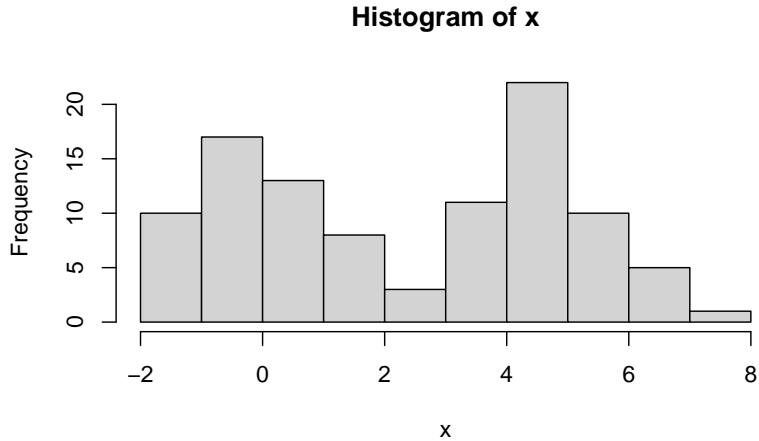
```
x <- rnorm(n = 100, mean = 5, sd = 1)
hist(x)
```



We can also input a vector instead of a single value for the `mean` or `sd` arguments if we want each sample to come from its own normal distribution. As an example, below we generate

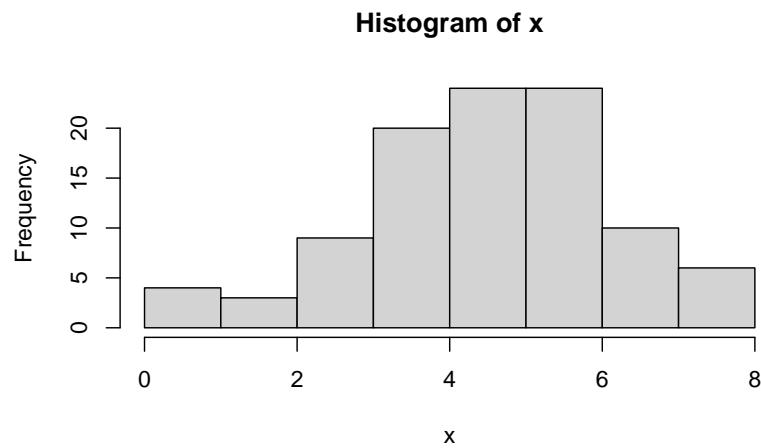
100 random numbers with the default standard deviation of 1 where half of the samples have mean 0 and the other half have mean 5.

```
x <- rnorm(n = 100, mean = rep(c(0,5),50))
hist(x)
```



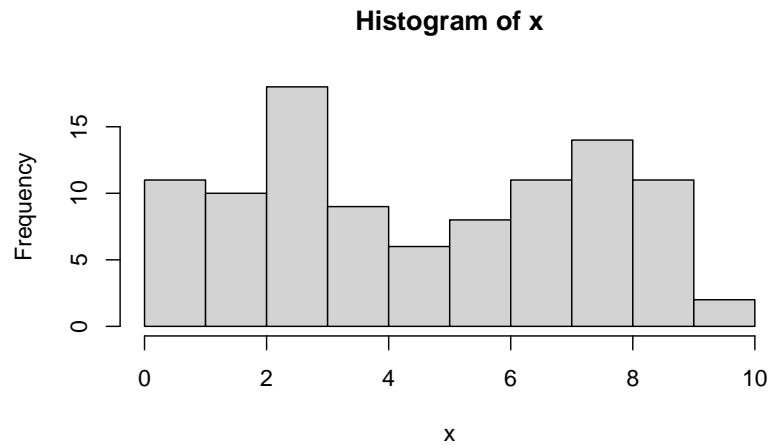
For the binomial distribution, the difference is that we need to specify a probability  $p$  and number of trials  $\text{size}$  (rather than  $\text{mean}$  and  $\text{sd}$  in the normal case) to specify the distribution. Below, we generate 100 random numbers following a binomial distribution with 10 trials and probability 0.5.

```
x <- rbinom(n = 100, p = 0.5, size = 10)
hist(x)
```



We can also specify a different size or probability of success for each sample. Below, we repeat our sample but this time let the probability of success be 0.25 for half of the sample and 0.75 for the other half.

```
x <- rbinom(n = 100, p = rep(c(0.25, 0.75), 50), size = 10)
hist(x)
```



### 8.1.2 Density Function

Next, we look at the density function. Recall that the probability density function for a normal distribution with mean  $\mu$  and standard deviation  $\sigma$  is given by the following formula:

$$f_X(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right)$$

Below, we can compare some of the values from the `dnorm()` function to this equation and see that they are in fact equal. You can also specify the mean and standard deviation in this function. Below we use the default values (mean = 0 and sd = 1).

```
dnorm(0) == 1/sqrt(2*pi)
#> [1] TRUE
dnorm(1) == exp(-1/2)/sqrt(2*pi)
#> [1] TRUE
dnorm(2) == exp(-1/2*2^2)/sqrt(2*pi)
#> [1] TRUE
```

If we wanted to find the density function for several values, we can input a vector to this density function. Below we find the values of the density function for a normal distribution with mean 1 and standard deviation 2 for values `c(-1, 0, 1, 2, 3)`.

```
dnorm(c(-1,0,1,2,3), mean = 1, sd = 2)
#> [1] 0.121 0.176 0.199 0.176 0.121
```

For the binomial distribution, `dbinom()` will return the probability of a certain number of successes and corresponds to the probability density function

$$P(X = x) = \binom{\text{size}}{x} p^x (1-p)^{\text{size}-x}.$$

Below, we find the probability of getting exactly 3 heads from 10 coin flips, each with a probability of 0.5 for heads.

```
dbinom(3, size = 10, p = 0.5)
#> [1] 0.117
```

While `dnorm()` allows us to specify any continuous values for  $x$ , `dbinom()` will give us a warning if  $x$  contains non-integer values since the support of a binomial variable only includes integers.

```

dbinom(2.4, size = 10, p = 0.5)
#> Warning in dbinom(2.4, size = 10, p = 0.5): non-integer x = 2.400000
#> [1] 0

```

We can also specify a vector for a distribution's parameters to find the distribution function for different distributions. For example, below I find the the probability density function for  $X = 4$  for the distribution with  $p = 0.25$  and  $p = 0.5$ .

```

dbinom(4, size = 10, p = c(0.25, 0.5))
#> [1] 0.146 0.205

```

### 8.1.3 Cumulative Distribution

Next, we take a look at the cumulative distribution function. For the normal distribution, the cumulative distribution is given by `pnorm()`, which takes in a value `x`, a `mean`, and a `sd` and returns the probability that a random variable following a  $N(\text{mean}, \text{sd})$  distribution is less than `x`. For example, for `x` equal to the mean, this will be a fifty percent probability because the normal distribution is symmetric with mean equal to the median. Below, we verify this for two different values of the mean.

```

pnorm(0)
#> [1] 0.5
pnorm(5, mean = 5, sd = 1)
#> [1] 0.5

```

Since the binomial distribution is discrete, it can only take on integer values from 0 to `size`. This means that, for example, the `pbinom()` function will return the same value for 3, 3.5, 3.6, all the way up to, but not including, 4 - this is because  $P(X \leq 3) = P(X \leq 3.2) = P(X \leq 3.5) = P(X \leq 3.6)$  and so on. Note that here we passed in a vector of values `x`.

```

pbinom(c(3, 3.5, 3.6, 4), size = 10, p = 0.5)
#> [1] 0.172 0.172 0.172 0.377

```

We can also vary the parameters for the distribution by passing a vector for `size` and/or `p` to the cumulative distribution function. Below, we find the probability that  $X \leq 3$  and the probability that  $X \leq 4$  with 12 trials and probability 0.25 and with 10 trials and probability 0.5.

```

pbinom(c(3, 3, 4, 4), size = c(12, 10, 12, 10), p=c(0.25, 0.5, 0.25, 0.5))
#> [1] 0.649 0.172 0.842 0.377

```

### 8.1.4 Quantile Distribution

Lastly, we have the quantile distribution function, which is the inverse of the cumulative distribution function. This function takes in a probability `x`, a `mean`, and a `sd` and returns the value for which the cumulative distribution function is equal to `x`. Thus, when `x` is equal to 0.5, the `qnorm()` function returns the median of the distribution, which is equal to the mean for the normal distribution.

```
qnorm(0.5)
#> [1] 0
qnorm(0.5, mean = 5, sd = 1)
#> [1] 5
```

For the discrete binomial distribution, the `qbinom()` function returns the largest integer value for which the probability of being less than or equal to that value is at most the inputted value `x`.

```
qbinom(c(0.2, 0.3), size = 10, p = 0.5)
#> [1] 2 3
```

### 8.1.5 Reference List for Probability Distributions

In the examples above, we only used the normal and binomial distributions - the other probability distributions available in R are given below. For each distribution, we have given the arguments for the `r[dist]()` function. The other three functions have a similar format. Unless otherwise stated, the parameter `n` is the number of observations.

- **Beta:** `rbeta(n, shape1, shape2, ncp = 0)` with shape parameters `shape1` and `shape2` (and optional non-centrality parameter `ncp`).
- **Binomial:** `rbinom(n, size, prob)` with probability of success `prob` and number of trials `size`
- **Cauchy:** `rcauchy(n, location = 0, scale = 1)` with location parameter `location` and scale parameter `scale`.
- **Chi-Square:** `rchisq(n, df, ncp = 0)` with `df` degrees of freedom and optional non-centrality parameter `ncp`.
- **Exponential:** `rexp(n, rate = 1)` with rate `rate` (i.e.,  $\text{mean} = 1/\text{rate}$ ).
- **F:** `rf(n, df1, df2, ncp)` with `df1` and `df2` degrees of freedom (and optional non-centrality parameter `ncp`).
- **Gamma:** `rgamma(n, shape, rate = 1, scale = 1/rate)` with parameters `shape` and `scale` (or alternatively specified by `rate`).
- **Geometric:** `rgeom(n, prob)` with probability parameter `prob`.

- **Hypergeometric:** `rhyper(nn, m, n, k)` with `m` white balls, `n` black balls, and `k` balls chosen.
- **Logistic:** `rlogis(n, location = 0, scale = 1)` with parameters `location` and `scale`.
- **Log Normal:** `rlnorm(n, meanlog = 0, sdlog = 1)` with mean `meanlog` and standard deviation `sdlog` on the log scale.
- **Negative Binomial:** `rnbinom(n, size, prob, mu)` with parameters `size` and `prob`.
- **Normal:** `rnorm(n, mean = 0, sd = 1)` with mean equal to `mean` and standard deviation equal to `sd`.
- **Poisson:** `rpois(n, lambda)` with parameter `lambda`.
- **Student t:** `rt(n, df, ncp)` with `df` degrees of freedom (and optional non-centrality parameter `ncp`).
- **Uniform:** `runif(n, min = 0, max = 1)` with minimum value `min` and maximum value `max`.
- **Weibull:** `rweibull(n, shape, scale = 1)` with parameters `shape` and `scale`.
- **Wilcoxon Rank Sum:** `rwilcox(nn, m, n)` with `nn` number of observations and sample sizes `m` and `n`.
- **Wilcoxon Signed Rank:** `rsignrank(nn, n)` with `nn` number of observations and sample size `n`.

### 8.1.6 Practice Question

Set the random seed to be 123, and then generate 5 random numbers following a [uniform distribution](#) with min 1 and max 5. Then, find the 0.15 quantile for this same distribution (it should be equal to 1.6).

```
# Insert your solution here:
```

## 8.2 Empirical Distributions and Sampling Data

At the start of this chapter, we used the `sample()` function. This function can also be used to sample from an empirical distribution. The `sample(x, size, replace=FALSE, prob=NULL)` function takes in the values we want to sample from `x`, the number of observations we want to sample `size`, and whether we want to sample with replacement `replace`. If we don't want to sample such that each value has an equal probability of being chosen, we can also set a probability vector `prob`, which must have the same length as `x`. Below we sample 500 rows without replacement from the `NHANESsample` data. To do so, we select 500 values from the indices 1 to the number of rows in the data. We then select rows of the data using these indices.

```

nhanes_sample_ids <- sample(1:nrow(NHANESsample), 500, replace=FALSE)
nhanes_sample <- NHANESsample[nhantes_sample_ids, ]
dim(nhantes_sample)
#> [1] 500 21

```

We now demonstrate sampling with replacement. By doing so, we create a new data set that is sampled from the empirical distribution of the data and that is called a *bootstrap sample*.

```

nhanes_sample_ids <- sample(1:nrow(NHANESsample), nrow(NHANESsample), replace=TRUE)
nhanes_sample <- NHANESsample[nhantes_sample_ids, ]
dim(nhantes_sample)
#> [1] 31265 21

```

Another way to sample from a data frame is to use the `slice_sample()` function from the tidyverse. In this function, we can either specify the number of observations to sample `n` or the proportion of observations to sample `prop`. Additionally, we can sample with or without replacement by setting the value of the argument `replace` (with default value FALSE). We use this function below to randomly sample 20% of observations without replacement.

```

nhantes_sample <- NHANESsample %>%
  slice_sample(prop = 0.2, replace = FALSE)
dim(nhantes_sample)
#> [1] 6253 21

```

### 8.2.1 Practice Question

Set the random seed to 5 and then sample 50 observations with replacement from the set of integers from 1 to 100. Take the mean of those observations - it should be 56.7.

```
# Insert your solution here:
```

Beyond sampling, we can also find the empirical cumulative distribution. That is, we can use a given vector to infer a distribution. In the case below, we draw a random sample from a normal distribution `vec` and then find its empirical cumulative distribution using the `ecdf()` function. This function actually returns a function, which can then be used to find the sample cumulative distribution for different values similar to the `p[dist]()` functions. Below, we find the sample probability that  $X \leq 0$ .

```

vec <- rnorm(100)
ecdf_vec <- ecdf(vec)
ecdf_vec(0)
#> [1] 0.63

```

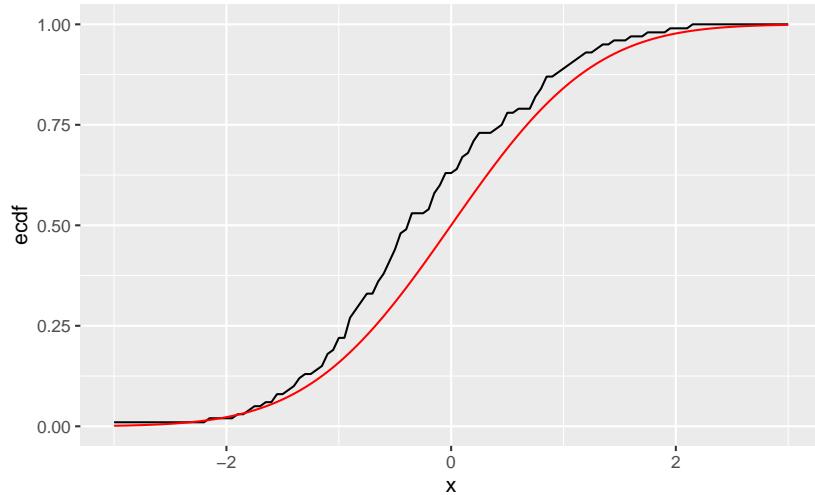
We plot this empirical distribution against the actual cdf using the `pnorm()` function below. Note that in order to do so, we create a sequence of possible `x` values to pass to both `pnorm()` and `ecdf_vec()`.

```

df <- data.frame(x = seq(-3, 3, 0.05))
df$ecdf <- ecdf_vec(df$x)
df$distn = pnorm(df$x)

ggplot(df) +
  geom_line(aes(x=x, y=ecdf), color = "black") +
  geom_line(aes(x=x, y=distn), color= "red")

```



In practice, the empirical cumulative distribution might involve data from a given data set that you want to use to represent the population's distribution. As an example, below we find the empirical distribution of blood lead level from the `NHANESsample` data frame. A blood lead level of 5 µg/dL or above is considered elevated. We can see 96.4% of observations have a blood lead level below this threshold.

```

ecdf_lead <- ecdf(nhanes_sample$LEAD)
ecdf_lead(5)
#> [1] 0.961

```

## 8.3 Recap Video

<https://www.youtube.com/embed/gi6nDWWRSeQ>

## 8.4 Exercises

1. Assume the distribution of female heights is approximated by a normal distribution with a mean of 64 inches and a standard deviation of 2.2 inches. Using this distribution, answer the following questions.
  - What is the probability that a randomly chosen female is 5 feet or shorter?
  - What is the probability that a randomly chosen female is 6 feet or taller?
  - Generate 500 random observations following this distribution and find the sample 0.15 quantile. Then, compare this to the 0.15 quantile using the `qdist()` function.
2. Compute the probability that the height of a randomly chosen female is within 1 SD from the average height.
3. Create a vector of 100 patient IDs, and then use the `sample()` function to assign half of them to a treatment group and the other half to a control group. Then, suppose those in the control group have a reduction in viral load distributed as  $X \sim 100 * \exp(\text{mean} = V)$ , where  $V$  follows a uniform distribution between 1 and 2, whereas those who are in the treatment group have a reduction in viral load distributed as  $X \sim 100 * \exp(\text{mean} = 3)$ . Plot distributions of reduction in viral load for both groups.

# 9 Hypothesis Testing

In this chapter, we will look at hypothesis testing in R. We will start with single sample distributions and tests, and then we will look at hypothesis tests for comparing two samples. Examples will include testing for positive correlations, performing two sample paired t-tests, and testing for equal variance among groups. The data we will use in this section comes from the Texas Health and Human Services Department and includes the reported number of induced terminations of pregnancy (ITOPs) from 2016 to 2021, stratified by both race and county. The data also contains the rate of abortions per 1000 females aged 15-49. Read the data documentation to see the full variable descriptions.

We will use the `tidyverse`, `gt`, and `gtsummary` packages to help manipulate and summarize the data. The `car` package contains the function `leveneTest()` to implement a Levene's test for homogeneity of variance across groups, and all other hypothesis tests are available in base R.

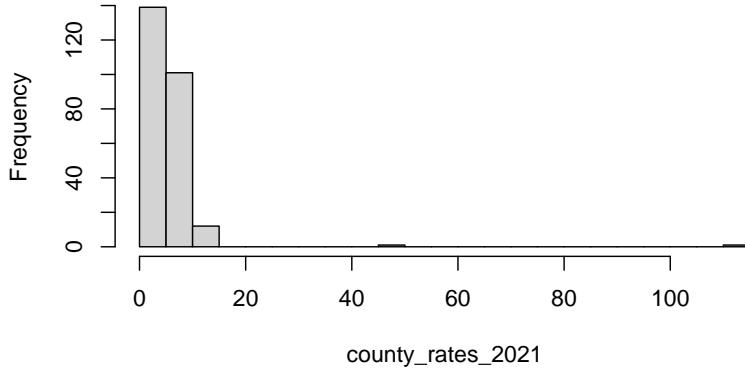
```
suppressPackageStartupMessages(library(tidyverse))
suppressPackageStartupMessages(library(car))
suppressPackageStartupMessages(library(HDSinRdata))
suppressPackageStartupMessages(library(gt))
suppressPackageStartupMessages(library(gtsummary))
data(tex_itop)
```

## 9.1 Univariate Distributions and One Sample Tests

Let's begin by looking at a single outcome of interest - the number of induced terminations of pregnancy (referred to as ITOPs or abortions below) in 2021 per 1000 females ages 15-49 in each county. We use the number of females ages 15-49 as a proxy to scale the number of abortions by the population size, though this is not truly reflective of the number of people who can give birth in each county.

```
county_rates_2021 <- tex_itop$total_rate[tex_itop$year == 2021]
hist(county_rates_2021, breaks = 35)
```

Histogram of county\_rates\_2021



We can see in the figure that this is a heavy-tailed distribution. Below, we find the 10 counties with the highest rates and see that there are some counties that very few total abortions but that have some of the highest abortion rates. This indicates a small population. On the other hand, we also observe Harris county, which contains the city of Houston and has both a high total abortion count and a high abortion rate.

```
tex_itop %>%
  filter(year==2021) %>%
  slice_max(n=10, total_rate) %>%
  dplyr::select(c(county, total_itop, total_rate))
#> # A tibble: 10 x 3
#>   county  total_itop total_rate
#>   <chr>      <dbl>     <dbl>
#> 1 Loving        1     111.
#> 2 Terrell       5      50
#> 3 Concho        4     13.9
#> 4 Harris      14122    13.5
#> 5 Irion         3     12.9
#> # i 5 more rows
```

Some of the counties are so small that we may want to consider dropping them from our analysis. In particular, the rates in Loving County and Terrel County are so high that we might consider them to be outliers. For this one sample analysis, however, we do not remove them. If we wanted to estimate the mean abortion rate among counties  $\mu$  we can do so by simply using the `mean()` function. For reference, the [CDC](#) estimated the national abortion rate in 2020 to be 11.2 abortions per 1,000 women aged 15–44 years.

```
mean(county_rates_2021, na.rm=TRUE)
#> [1] 5.17
```

Within R we can also calculate a confidence interval for this mean. Recall that a  $(1 - \alpha)\%$  confidence interval for the mean is given by the equation  $\hat{\mu} \pm z_{1-\alpha/2} \cdot \frac{\hat{\sigma}}{\sqrt{n}}$ , where  $\hat{\mu}$  is our sample mean,  $\hat{\sigma}^2$  is the sample variance, and  $n$  is the number of observations.

Below, we use this formula to calculate a 95% confidence interval for the mean abortion rate among counties:

```
est_mean <- mean(county_rates_2021, na.rm=TRUE)
est_sd <- sd(county_rates_2021)
z_alpha <- dnorm(1-0.05/2)
n <- length(county_rates_2021)
c(est_mean - z_alpha*est_sd/sqrt(n), est_mean + z_alpha*est_sd/sqrt(n))
#> [1] 5.04 5.29
```

If we want to display this nicely, we can use the `round()` function, which allows us to specify a number of digits to be displayed, and the `paste()` function, which creates a single character string from multiple inputs.

```
lower <- round(est_mean - z_alpha*est_sd/sqrt(n), 3)
upper <- round(est_mean + z_alpha*est_sd/sqrt(n), 3)
paste("Confidence Interval: (", lower, ", ", upper, ")")
#> [1] "Confidence Interval: ( 5.044 , 5.289 )"
```

Suppose that we wanted to run a hypothesis test to compare the mean to a pre-determined value. In particular, the Texas Heartbeat Act was introduced in 2021 and drastically reduced the number of eligible abortions. We could test whether there were significantly fewer abortions in 2021 compared to 2020 using a one-sided t-test. Our null hypothesis is that  $\mu \geq 6.23$ , the mean abortion rate in 2020. To run this hypothesis test, we use the `t.test()` function. For a one sample t-test, we need to specify our sample `x`, the alternative hypothesis `alternative` (default is a two-sided test), the true value of the mean `mu` (default 0), and a confidence level `conf.level` (default 0.95). Below, we run this t-test, and we can see from the result that we reject the null hypothesis at the 0.05 level and observe a statistically significant decline in the abortion rate in 2021.

```
t.test(county_rates_2021, alternative = "less", mu = 6.23,
       conf.level=0.95)
#>
#> One Sample t-test
#>
```

```
#> data: county_rates_2021
#> t = -2, df = 253, p-value = 0.02
#> alternative hypothesis: true mean is less than 6.23
#> 95 percent confidence interval:
#> -Inf 5.98
#> sample estimates:
#> mean of x
#>      5.17
```

The output for this test is printed above. If we want to reference these values, we will need to save the result. The object `t_test_res` is a list that contains information about the statistic, p-value, confidence interval, etc. The list of outputs are similar to other test objects, so it is useful to look at what is contained in each by reading the test documentation (`?t.test`). Below, we find the p-value from `t_test_res`.

```
t_test_res <- t.test(county_rates_2021, alternative = "less", mu = 6.23,
                     conf.level=0.95)
names(t_test_res)
#> [1] "statistic"    "parameter"    "p.value"      "conf.int"
#> [5] "estimate"     "null.value"   "stderr"       "alternative"
#> [9] "method"        "data.name"

t_test_res$p.value
#> [1] 0.0161
```

### 9.1.1 Practice Question

Test whether there were significantly more abortions in 2019 compared to 2020 using a one-sided t-test. Your test statistic should be -6.4736.

```
# Insert your solution here:
```

One thing to consider is that the `t.test()` function assumes that the sample `x` comes from a normal distribution. The one-sample Wilcoxon signed rank test is a non-parametric alternative to the one-sample t-test that can be used to compare the median value of a sample to a theoretical value without assuming that the data is normally distributed. This test can be performed using the `wilcox.test()` function and takes in the same arguments as the `t.test()` function. Below, we can see that we again reject the null hypothesis at the 0.05 level and conclude that the median abortion rate in 2021 was significantly lower than 5.14, which was the median rate in 2020.

```
wilcox_res <- wilcox.test(county_rates_2021, alternative = "less",
                           mu = 5.14, conf.level=0.95)
wilcox_res
#>
#> Wilcoxon signed rank test with continuity correction
#>
#> data: county_rates_2021
#> V = 12807, p-value = 0.002
#> alternative hypothesis: true location is less than 5.14
wilcox_res$p.value
#> [1] 0.00193
```

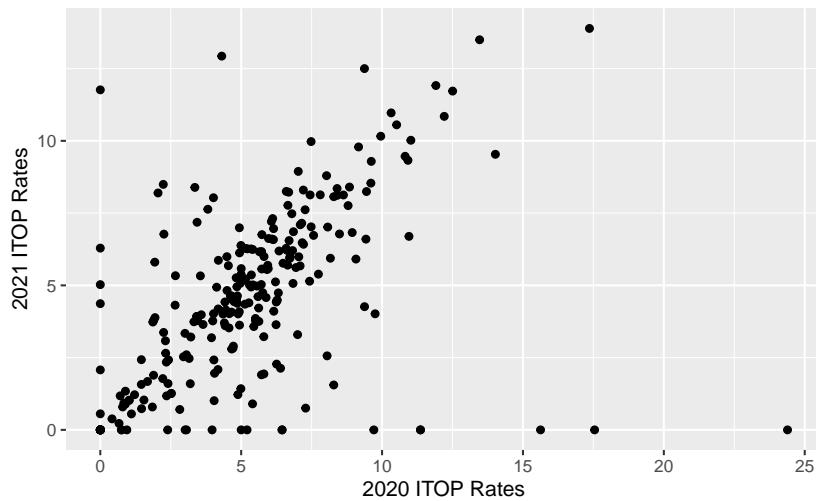
## 9.2 Correlation and Covariance

We now look at two sample tests. To start, we look at the 2020 and 2021 rates by county. We pivot our data into a wider format in order to create 2020 and 2021 rate columns, and, this time, we filter out the Loving and Terrel counties to remove outliers. We then create a scatter plot of 2021 vs. 2020 rates and observe a linear correlation between the two.

```
county_rates <- tex_itop %>%
  dplyr::select(c(county, total_rate, year)) %>%
  filter(!(county %in% c("Terrell", "Loving")),
         year %in% c(2020, 2021)) %>%
  pivot_wider(names_from = year, values_from = total_rate) %>%
  na.omit() %>%
  rename("y2020"="2020", "y2021"="2021")
head(county_rates)
#> # A tibble: 6 x 3
#>   county    y2020   y2021
#>   <chr>     <dbl>   <dbl>
#> 1 Anderson  6.84   5.07
#> 2 Andrews   1.85   0.792
#> 3 Angelina  5.81   6.00
#> 4 Aransas   3.44   7.18
#> 5 Archer    1.47   0.733
#> # i 1 more row

ggplot(county_rates) +
  geom_point(aes(x=y2020,y=y2021)) +
```

```
labs(x="2020 ITOP Rates", y="2021 ITOP Rates")
```



We have seen before how to calculate the correlation between two columns using the `cor()` function. We can also calculate the covariance using the `cov()` function. As suspected, there is a positive correlation. The estimated covariance is around 5.2.

```
cor(county_rates$y2020, county_rates$y2021)
#> [1] 0.5
cov(county_rates$y2020, county_rates$y2021)
#> [1] 5.2
```

Besides calculating the value of the correlation, we can also test whether this correlation is significantly different from zero. The function `cor.test()` tests for association between paired samples, using either Pearson's product moment correlation coefficient, Kendall's  $\tau$ , or Spearman's  $\rho$ . Similar to the `t.test()` and `wilcox.test()` functions, we can also specify the `alternative` and `conf.level` arguments. Below, we test whether there is a non-zero correlation between the 2020 and 2021 county rates using Pearson's product-moment correlation. We can see from the resulting p-value that we can reject the null hypothesis that the correlation is zero and conclude that it is instead significantly different than zero. This time we also print the computed confidence interval for our estimate.

```
cor_test_res <- cor.test(county_rates$y2020,
                         county_rates$y2021, method="pearson")
cor_test_res
#>
```

```

#> Pearson's product-moment correlation
#>
#> data: county_rates$y2020 and county_rates$y2021
#> t = 9, df = 250, p-value <2e-16
#> alternative hypothesis: true correlation is not equal to 0
#> 95 percent confidence interval:
#> 0.401 0.587
#> sample estimates:
#> cor
#> 0.5

cor_test_res$conf.int
#> [1] 0.401 0.587
#> attr(,"conf.level")
#> [1] 0.95

```

## 9.3 Two Sample Tests for Continuous Variables

If we wanted to directly compare the difference between 2020 and 2021 rates, we could use a two sample test. In this case, because our samples are paired by county, we can use a two sample paired t-test. Specifically, we use a two-sided test to test the null hypothesis that the rates are equal by specifying two different vectors `x` and `y`. Note that we used the default values of `mu=0` and `alternative="two.sided"`. Additionally, we used the default value `var.equal=FALSE`, which implies that the samples may have different variances. From the results below, we reject the null hypothesis that the two county rates are equal at the 0.05 level. We also print a 95% confidence interval of the difference in means.

```

t_test_two_res <- t.test(x=county_rates$y2020, y=county_rates$y2021)
t_test_two_res
#>
#> Welch Two Sample t-test
#>
#> data: county_rates$y2020 and county_rates$y2021
#> t = 2, df = 497, p-value = 0.01
#> alternative hypothesis: true difference in means is not equal to 0
#> 95 percent confidence interval:
#> 0.145 1.278
#> sample estimates:
#> mean of x mean of y

```

```

#>      5.28      4.57
t_test_two_res$conf.int
#> [1] 0.145 1.278
#> attr(,"conf.level")
#> [1] 0.95

```

In the `tex_itop` dataset, each county has also been categorized by whether it was urban or rural. Suppose we want to compare the change in abortion rates from 2020 to 2021 between rural and urban counties. First, we create a variable describing the rate change between these years using the code below. We choose to use the change in rate rather than percent change to avoid infinite or undefined values.

```

county_rates_type <- tex_itop %>%
  dplyr::select(c(county, urban, county_type, total_rate, year)) %>%
  filter(total_rate < 15, year %in% c(2020, 2021)) %>%
  pivot_wider(names_from = year, values_from = total_rate) %>%
  na.omit() %>%
  rename("y2020"="2020", "y2021"="2021") %>%
  mutate(rate_change = (y2021-y2020))

```

We again use a two-sample two-sided t-test, but this time the data is not paired. Below, we show an alternative way to specify a t-test test below using a formula `lhs ~ rhs`, where `lhs` is a numeric column and `rhs` is a factor column with two levels. We must also specify the data in this case. From the R output in this case, we would fail to reject the null hypothesis at the 0.05 level and conclude that the rate changes for urban and rural counties are not significantly different. We also print the estimates used in the t-test using `estimate`, which shows the estimated mean in both groups.

```

t_test_unpaired <- t.test(rate_change~urban, data=county_rates_type)
t_test_unpaired
#>
#> Welch Two Sample t-test
#>
#> data: rate_change by urban
#> t = 0.1, df = 205, p-value = 0.9
#> alternative hypothesis: true difference in means between group Rural and group Urban is
#> 95 percent confidence interval:
#> -0.495 0.563
#> sample estimates:
#> mean in group Rural mean in group Urban
#>           -0.469             -0.503

```

```
t_test_unpaired$estimate
#> mean in group Rural mean in group Urban
#>           -0.469            -0.503
```

Note that this yields the same results as if we had specified the data using two vectors `x` and `y`.

```
x <- county_rates_type$rate_change[county_rates_type$urban == 'Urban']
y <- county_rates_type$rate_change[county_rates_type$urban == 'Rural']
t.test(x=x, y=y, paired = FALSE)
#>
#> Welch Two Sample t-test
#>
#> data: x and y
#> t = -0.1, df = 205, p-value = 0.9
#> alternative hypothesis: true difference in means is not equal to 0
#> 95 percent confidence interval:
#> -0.563 0.495
#> sample estimates:
#> mean of x mean of y
#> -0.503    -0.469
```

Besides a t-test, we can also use a two-sample Wilcoxon non-parametric test using the `wilcox.test()` function, which has the same arguments as the function `t.test()`. Both the `t.test()` and `wilcox.test()` can only compare two groups. When we want to compare two or more independent samples, we can use a Kruskal-Wallis rank sum test using the `kruskal.test()` function or a one-way analysis of variance (ANOVA) using the `aov()` function.

This time we use the column `county_type`, which is an indicator for whether the county is urban, suburban, or rural according to the RUCC (rural-urban continuum codes) from the U.S. Department of Agriculture. For the `kruskal.test()` function, we can either specify the arguments `formula (rate_change ~ county_type)` and `data (county_rates_type)` or we can specify two vectors: `x`, a numeric vector, and `g`, a factor representing the group. For the `aov()` function, we specify the test using a formula and the data. To see the p-value, we have to use the `summary()` function to print the result. Again, both tests suggest that we fail to reject the null hypothesis at the 0.05 level.

```
kruskal.test(county_rates_type$rate_change,
             county_rates_type$county_type)
#>
#> Kruskal-Wallis rank sum test
```

```

#>
#> data: county_rates_type$rate_change and county_rates_type$county_type
#> Kruskal-Wallis chi-squared = 2, df = 2, p-value = 0.3

aov_res <- aov(rate_change~county_type, data=county_rates_type)
summary(aov_res)

#>           Df Sum Sq Mean Sq F value Pr(>F)
#> county_type    2     7    3.36    0.53   0.59
#> Residuals    245 1547    6.31

```

### 9.3.1 Practice Question

Use an appropriate test to determine whether the ITOP rates in 2016 significantly differed by race. The test statistic should be 264.27 with associated p-value < 2.2e-16.

```
# Insert your solution here:
```

### 9.3.2 Two Sample Variance Tests

We could also test whether the variance of a continuous variable is equal between groups. To start, we compare the variance in abortion rates in 2021 between urban and rural counties using an F test. Our null hypothesis for this test is that the variance in both groups is equal. The function `var.test()` implements an F test and has the same main arguments as the `t.test()` function: vectors `x` and `y` OR a `formula` and `data`, the alternative hypothesis `alternative`, and `conf.level`. Additionally, we can specify the hypothesized ratio of the variances through the argument `ratio` (default value 1). Note that this function assumes that the two samples come from normally distributed populations. We fail to reject the null hypothesis that the variance in rates are equal at the 0.05 level and print the estimate of the ratio of variances, which is around 1.11.

```

f_test <- var.test(y2021 ~ urban, county_rates_type)
f_test
#>
#> F test to compare two variances
#>
#> data: y2021 by urban
#> F = 1, num df = 187, denom df = 59, p-value = 0.6
#> alternative hypothesis: true ratio of variances is not equal to 1
#> 95 percent confidence interval:

```

```

#> 0.719 1.657
#> sample estimates:
#> ratio of variances
#> 1.12
f_test$estimate
#> ratio of variances
#> 1.12

```

Lastly, we implement a Levene's test to test whether group variances are equal when there are more than two groups. This test can be specified using a formula and data set, as below, or by providing two vectors `y`, a numeric vector, and `g`, a vector specifying the groups. This test is from the `car` package and has slightly different output than other tests. In particular, to access the p-value, we need to access the value named '`Pr(>F)`'. In this case, we actually do reject the null hypothesis at the 0.05 level.

```

levene_test <- leveneTest(y2021 ~ as.factor(county_type),
                           county_rates_type)
print(levene_test)
#> Levene's Test for Homogeneity of Variance (center = median)
#> Df F value Pr(>F)
#> group  2    3.41  0.034 *
#>        245
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
levene_test[['Pr(>F)']]
#> [1] 0.0345      NA

```

## 9.4 Two Sample Tests for Categorical Variables

In the two sample tests above, we were comparing the distributions of continuous variables. We now look at comparing distributions of categorical variables. We will first categorize counties by their abortion rate in 2020 being above or below 11.2, which was the national average rate that year. We display the distribution of this variable by the urban/rural grouping using a contingency table below.

```

county_rates_type$below_nat_avg <-
  ifelse(county_rates_type$y2020 > 11.2, "Above Nat Avg",
         "Below Nat Avg")
table(county_rates_type$below_nat_avg, county_rates_type$urban)
#>

```

```
#>          Rural Urban
#> Above Nat Avg     3     4
#> Below Nat Avg   185    56
```

We can use a Fisher's exact test to test whether the classifications of being above and below the national average and being rural and urban are associated with each other. In this case, the null hypothesis is that the odds or being below the national average is equal between rural and urban counties. The `fisher.test()` function can either take in a contingency table as a matrix or can be specified by two factor vectors `x` and `y`, which is how we implement it below. Additionally, there is the option to specify the `alternative` and `conf.level` arguments. We do not see a statistically significant difference between urban and rural counties at the 0.05 level with the estimated odds ratio is around 0.23.

```
fisher_test <- fisher.test(county_rates_type$urban,
                           county_rates_type$below_nat_avg)
fisher_test
#>
#> Fisher's Exact Test for Count Data
#>
#> data: county_rates_type$urban and county_rates_type$below_nat_avg
#> p-value = 0.06
#> alternative hypothesis: true odds ratio is not equal to 1
#> 95 percent confidence interval:
#>  0.0325 1.3955
#> sample estimates:
#> odds ratio
#>      0.229
fisher_test$estimate
#> odds ratio
#>      0.229
```

An alternative test is a Pearson's Chi-Squared test, which can be used for large sample sizes. The counts of rural and urban counties in the 'Above Nat Avg' category are very small, so we recategorize our outcome to be at or above Texas's average to avoid this complication. The `chisq.test()` function also takes in a contingency table as a matrix or can be specified by two factor vectors `x` and `y`. Another useful argument is `correct` (default is TRUE) which indicates whether to apply a continuity correction. For this test, we observe a statistically significant difference in the proportion of counties above the national average between rural and urban counties and reject the null hypothesis at the 0.05 level.

```

tex_mean <- mean(county_rates_type$y2020)
county_rates_type$below_tex_avg <-
  ifelse(county_rates_type$y2020 > tex_mean, "Above Texas Ave",
         "Below Texas Ave")
table(county_rates_type$below_tex_avg, county_rates_type$urban)
#>
#>           Rural   Urban
#> Above Texas Ave     84     39
#> Below Texas Ave    104     21

chi_sq <- chisq.test(county_rates_type$below_tex_avg,
                      county_rates_type$urban)
chi_sq
#>
#> Pearson's Chi-squared test with Yates' continuity correction
#>
#> data: county_rates_type$below_tex_avg and county_rates_type$urban
#> X-squared = 7, df = 1, p-value = 0.01
chi_sq$p.value
#> [1] 0.00953

```

#### 9.4.1 Practice Question

Repeat the Chi-Squared test, but this time use the RUCC codes instead of the `urban` column. You should get a p-value of 0.2799. Think about what could explain the difference between these results.

```
# Insert your solution here:
```

## 9.5 Adding Hypothesis Tests to Summary Tables

In [Chapter 4](#), we used the `gt` and `gtsummary` packages to create summary tables of variables. When creating a stratified table (done by add the `by` argument), we can automatically add p-values for hypothesis tests comparing across populations using the `add_p()` function. By default, the `add_p()` function uses a Kruskal-Wallis rank sum test for continuous variables (or a Wilcoxon rank sum test when the `by` variable has two levels) and uses a Chi-Squared Contingency Table Test for categorical variables (or a Fisher's Exact Test for categorical variables with any expected cell count less than five). The chosen test(s) are displayed as footnotes.

```

tbl_summary(tex_itop, include = c(total_rate, white_rate, asian_rate,
                                 hispanic_rate, black_rate,
                                 native_american_rate),
            by = "year", statistic = list(all_continuous() ~ "{mean} ({sd})")) %>%
add_p() %>%
as_gt() %>%
gt:::as.tags.gt_tbl()

```

Characteristic	2016, N = 254 <sup>1</sup>	2017, N = 254 <sup>1</sup>	2018, N = 254 <sup>1</sup>	2019, N = 254 <sup>1</sup>	2020, N =
total_rate	4.8 (3.0)	4.9 (4.9)	5.3 (4.2)	4.9 (3.3)	6.2 (14.1)
white_rate	4.7 (3.8)	5.1 (5.8)	5.4 (6.0)	5.1 (5.1)	6.8 (21.3)
asian_rate	7 (32)	12 (46)	8 (21)	7 (20)	14 (55)
hispanic_rate	3.9 (3.7)	4.7 (6.3)	4.6 (4.6)	4.6 (5.0)	4.6 (5.8)
black_rate	9 (21)	13 (65)	26 (153)	20 (80)	25 (111)
native_american_rate	5.0 (24.0)	9.3 (65.0)	4.9 (17.8)	2.3 (12.4)	4.1 (21.1)

<sup>1</sup> Mean (SD)

<sup>2</sup> Kruskal-Wallis

rank sum test

We observe that a Kruskal-Wallis rank sum test was used to compare abortion rates across year for each racial group. All of the reported p-values are above 0.05 so overall it indicates that there were not statistically significant changes across years in the abortion rate.

## 9.6 Recap Video

<https://www.youtube.com/embed/3vyCeUdSS6U>

## 9.7 Exercises

For the following exercises, we will be using the `pain` data from the `HDSinRdata` package.

```
data(pain)
```

1. Determine whether the presence or absence of follow-up information is significantly associated with the initial average pain intensity. What do the results suggest?

2. First, plot PROMIS\_PAIN\_BEHAVIOR grouped by race (you can use the PAT\_RACE\_CAT variable that we defined in [Chapter 7](#)). What do you observe? Next, choose an appropriate test to determine whether this variable differs significantly by race.
3. Examine the association between CCI\_BIN and MEDICAID\_BIN. Are these variable significantly related to each other? How would you describe their relationship?
4. Recreate the summary table below. Then, recreate the p-values for PROMIS\_DEPRESSION, PROMIS\_ANXIETY, and MEDICAID\_BIN using the appropriate tests.

# **Part IV**

# **Regression**

# 10 Linear Regression

This chapter will introduce you to linear regression analysis in R. We will cover how to fit linear regression models, check model assumptions using diagnostic plots, change model formulas by adding transformations and interactions, calculate performance metrics, and perform variable selection using stepwise selection.

For this chapter, we will use the `NHANESsample` dataset, which was retrieved from the National Health and Nutrition Examination Survey ([NHANES](#)) and is in the `HDSinRdata` package. The sample contains lead, blood pressure, BMI, smoking status, alcohol use, and demographic variables from NHANES 1999-2018. Variable selection and feature engineering were conducted in an effort to replicate the regression analyses conducted by [Huang, Z. \(2022\). Association Between Blood Lead Level With High Blood Pressure in US \(NHANES 1999-2018\). Frontiers in Public Health, 892](#). Use the help operator `?NHANESsample` to read the variable descriptions. Note that we ignore survey weights for this analysis.

We will use the `broom` package to present the estimated coefficients for our regression models and the `car` package to compute variance inflation factors.

```
suppressPackageStartupMessages(library(HDSinRdata))
suppressPackageStartupMessages(library(tidyverse))
suppressPackageStartupMessages(library(broom))
suppressPackageStartupMessages(library(car))
data(NHANESsample)
```

## 10.1 Simple Linear Regression

In [Chapter 4](#), we presented some initial exploratory analysis for this data. In this chapter, we will use linear regression to understand the association between blood lead levels and systolic blood pressure, adjusting for possible confounders. Replicating the analysis of [Huang](#), we create summary columns for systolic and diastolic blood pressure. If an observation has one blood pressure reading, then we use that value. If there is more than one blood pressure reading, then we drop the first observation and average the rest. We do a complete case analysis by dropping any observation with NA values. This leaves us with 30,405 observations.

```

NHANESsample$SBP <- apply(NHANESsample[,c("SBP1", "SBP2", "SBP3", "SBP4")], 1,
  function(x) case_when(sum(!is.na(x)) == 0 ~ NA,
                        sum(!is.na(x)) == 1 ~ sum(x, na.rm=TRUE),
                        sum(!is.na(x)) > 1 ~ mean(x[-1], na.rm=TRUE)))
NHANESsample$DBP <- apply(NHANESsample[,c("DBP1", "DBP2", "DBP3", "DBP4")], 1,
  function(x) case_when(sum(!is.na(x)) == 0 ~ NA,
                        sum(!is.na(x)) == 1 ~ sum(x, na.rm=TRUE),
                        sum(!is.na(x)) > 1 ~ mean(x[-1], na.rm=TRUE)))
nhanes_df <- na.omit(subset(NHANESsample, select= -c(SBP1, SBP2, SBP3, SBP4,
                                                       DBP1, DBP2, DBP3, DBP4)))
dim(nhanes_df)
#> [1] 30405      15

```

Next, we make sure any categorical variables are coded as factors.

```

nhanes_df$SEX <- as.factor(nhanes_df$SEX)
nhanes_df$RACE <- as.factor(nhanes_df$RACE)
nhanes_df$EDUCATION <- as.factor(nhanes_df$EDUCATION)
nhanes_df$BMI_CAT <- as.factor(nhanes_df$BMI_CAT)
nhanes_df$LEAD_QUANTILE <- as.factor(nhanes_df$LEAD_QUANTILE)

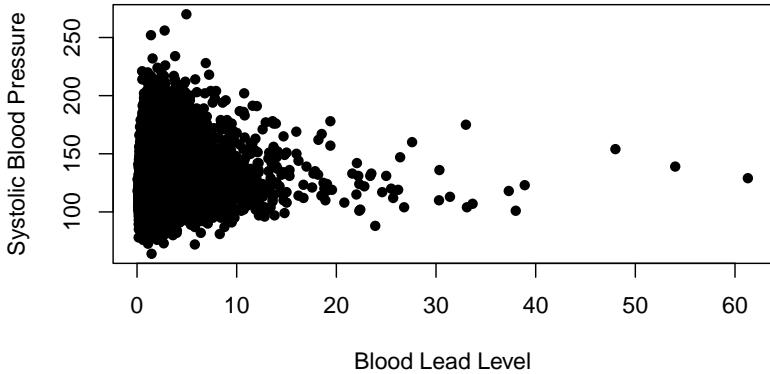
```

We will start with simple linear regression. Below, we plot the relationship between blood lead level and systolic blood pressure. For a simple linear regression scenario with a single continuous independent variable, a scatter plot allows us to easily visualize whether we meet the assumptions underlying linear regression. The survey sampling for the NHANES survey allows us to assume that each observation is independent. Looking at the plots below, we expect to see that the average systolic blood pressure increases linearly with blood lead level and that the observations look normally distributed with equal variance along that line. Below, we do not observe that to be the case. We will come back to this in the section on transformations and interactions.

```

plot(nhanes_df$LEAD, nhanes_df$SBP,
      xlab = "Blood Lead Level", ylab = "Systolic Blood Pressure", pch=16)

```



Despite our observations above, we will continue by fitting a simple linear regression model to explain the association between SBP and LEAD. The function `lm(formula = y ~ x, data)` fits a linear model in R. The first argument is the formula of the linear model: on the left hand side of the `~` we put the outcome variable, and on the right hand side we put the independent variable. When we have multiple independent variables we separate them with a `+` (e.g. `y~x1+x2`). The output of this function is an `lm` object.

We can call the `summary()` function on this object to print a summary of the model, which includes the estimated coefficients, information about the residuals, the R-squared and adjusted R-squared values, and the F-statistic. Recall, that we previously used the `summary()` function to get summary statistics about a vector. This is an example of how multiple functions can have the same name. R figures out which `summary()` function to use by identifying that the argument we passed in is a `lm` object.

```
simp_model <- lm(formula = SBP~LEAD, data = nhanes_df)
summary(simp_model)
#>
#> Call:
#> lm(formula = SBP ~ LEAD, data = nhanes_df)
#>
#> Residuals:
#>     Min      1Q  Median      3Q     Max
#> -96.36 -12.52  -2.79   9.36 140.88
#>
#> Coefficients:
#>             Estimate Std. Error t value Pr(>|t|)
#> (Intercept) 120.665     0.149   807.1   <2e-16 ***
#>
```

```

#> LEAD          1.708      0.058     29.4   <2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 18.5 on 30403 degrees of freedom
#> Multiple R-squared:  0.0277, Adjusted R-squared:  0.0277
#> F-statistic:  867 on 1 and 30403 DF,  p-value: <2e-16

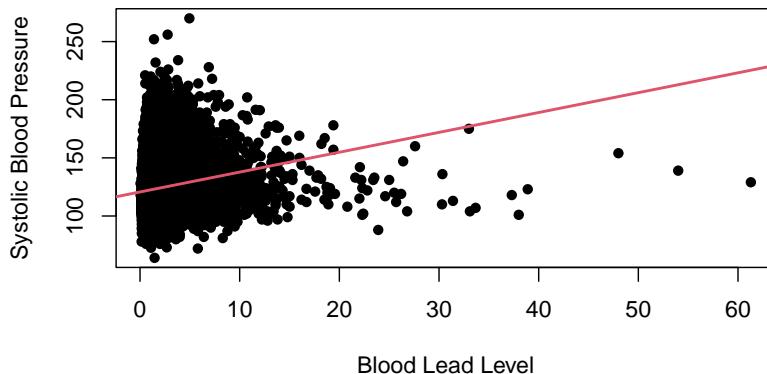
```

To visualize this model, we can add the estimated regression line to our scatter plot from above. In `ggplot2`, this can be done with the `geom_smooth()` function. In base R, we use the `abline()` function, which can take in a regression model as an input. We can see that the estimated regression line does not fit our data very well.

```

plot(nhanes_df$LEAD, nhanes_df$SBP,
      ylab=c("Systolic Blood Pressure"),
      xlab=c("Blood Lead Level"), pch=16)
abline(simp_model, col=2, lwd=2)

```



### 10.1.1 Practice Question

Fit a simple linear regression model with `SBP` as the outcome and `AGE` as the independent variable. The estimated coefficient for `AGE` should be 0.47693. Then, plot these two variables against each other and add the estimated regression line to the plot, as we did above. You should see that this regression has a better fit than the previous one.

```
# Insert your solution here:
```

## 10.2 Multiple Linear Regression

We now create a model that is similar to the previous one except that it also adjusts for age and sex. To add these variables into the model, we have to specify a new formula. Below, we fit this model and then print a summary, again using the `summary()` function.

```
adj_model <- lm(SBP ~ LEAD + AGE + SEX, data = nhanes_df)
summary(adj_model)

#>
#> Call:
#> lm(formula = SBP ~ LEAD + AGE + SEX, data = nhanes_df)
#>
#> Residuals:
#>    Min      1Q Median      3Q     Max
#> -65.62 -10.59 -1.55  8.55 131.60
#>
#> Coefficients:
#>             Estimate Std. Error t value Pr(>|t|)
#> (Intercept) 101.78541   0.30353 335.34 < 2e-16 ***
#> LEAD         0.40007   0.05525   7.24  4.5e-13 ***
#> AGE          0.46193   0.00557  82.97 < 2e-16 ***
#> SEXFemale   -2.77774   0.19567 -14.20 < 2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 16.6 on 30401 degrees of freedom
#> Multiple R-squared:  0.212, Adjusted R-squared:  0.212
#> F-statistic: 2.72e+03 on 3 and 30401 DF, p-value: <2e-16
```

We can also extract the estimated regression coefficients from the model using the `coef()` function or by using the `tidy` function from the `broom` package. This function puts the coefficient estimates, standard errors, statistics, and p-values in a data frame. We can also add a confidence interval by specifying `conf.int = TRUE`. Below, we add a 95% confidence interval (which is the default value for `conf.level`).

```
coef(adj_model)
#> (Intercept)      LEAD       AGE     SEXFemale
```

```

#>      101.785       0.400       0.462      -2.778

tidy(adj_model, conf.int=TRUE, conf.level=0.95)
#> # A tibble: 4 x 7
#>   term      estimate std.error statistic p.value conf.low conf.high
#>   <chr>     <dbl>     <dbl>     <dbl>     <dbl>     <dbl>     <dbl>
#> 1 (Intercept) 102.      0.304     335.      0       101.      102.
#> 2 LEAD        0.400     0.0552    7.24     4.54e-13    0.292     0.508
#> 3 AGE         0.462     0.00557   83.0      0       0.451     0.473
#> 4 SEXFemale   -2.78     0.196    -14.2    1.36e-45   -3.16     -2.39

```

Some other useful summary functions are `resid()`, which returns the residual values for the model, and `fitted()`, which returns the fitted values or estimated y values. We can also predict on new data using the `predict()` function. Below we look at the distribution of the residual values and then plot the fitted vs. true values. We observe some extreme residual values as well as the fact that the absolute residual values increase with increased blood pressure values.

```

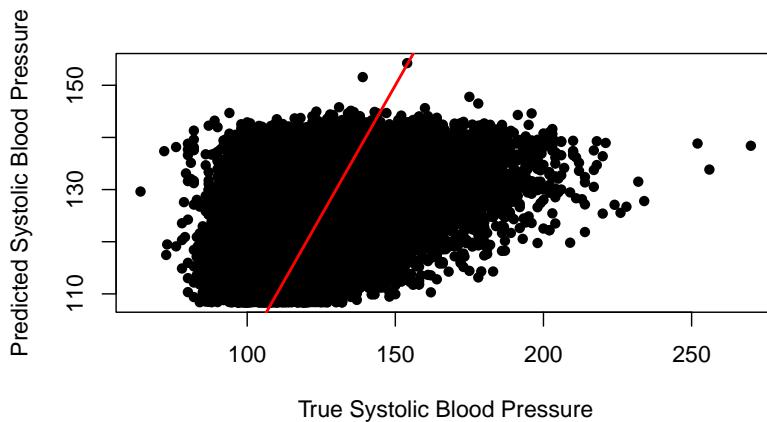
summary(resid(adj_model))
#>   Min. 1st Qu. Median   Mean 3rd Qu.   Max.
#> -65.6 -10.6  -1.6    0.0   8.5  131.6

```

```

plot(nhanes_df$SBP, fitted(adj_model),
      xlab = "True Systolic Blood Pressure",
      ylab="Predicted Systolic Blood Pressure", pch=16)
abline(a=0, b=1, col="red", lwd=2)

```



We can next perform a nested hypothesis test between our simple linear regression model and our adjusted model using the `anova()` function. We pass both models to this function along with the argument `test="F"` to indicate that we are performing an F-test. The `print()` function shows the two tested models along with the associated p-value, which indicates a significantly better fit for the adjusted model.

```
print(anova(simp_model, adj_model, test="F"))
#> Analysis of Variance Table
#>
#> Model 1: SBP ~ LEAD
#> Model 2: SBP ~ LEAD + AGE + SEX
#>   Res.Df   RSS Df Sum of Sq    F Pr(>F)
#> 1 30403 10375769
#> 2 30401  8413303  2   1962467 3546 <2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The model summary for the adjusted model displays the estimated coefficient for `sex` as `SEXFemale`, which indicates that the reference level for sex is male. If we want to change our reference level, we can reorder the factor variable either by using the `factor()` function and specifying `Female` as the first level or by using the `relevel()` function. The `ref` argument in the `relevel()` function specifies the new reference level. Now, when we run the model, we can see that the estimated coefficient for `sex` is labeled as `SEXMales`.

```
nhanes_df$SEX <- relevel(nhanes_df$SEX, ref="Female")
adj_model2 <- lm(SBP ~ LEAD + AGE + SEX, data = nhanes_df)
tidy(adj_model2)
#> # A tibble: 4 x 5
#>   term      estimate std.error statistic p.value
#>   <chr>      <dbl>     <dbl>     <dbl>     <dbl>
#> 1 (Intercept) 99.0      0.293     338.     0
#> 2 LEAD        0.400      0.0552    7.24    4.54e-13
#> 3 AGE         0.462      0.00557   83.0     0
#> 4 SEXMale     2.78       0.196    14.2     1.36e-45
```

The formula passed to the `lm()` function also allows us to use the `.` to indicate that we would like to include all remaining columns as independent variables or the `-` to exclude variables. Below, we show how we could use these to fit a model with `LEAD`, `AGE`, and `SEX` as included covariates by excluding all other variables instead of by specifying these three variables themselves.

```

lm(SBP ~ . - ID - RACE - EDUCATION - INCOME - SMOKE - YEAR - BMI_CAT -
    LEAD_QUANTILE - DBP - ALC - HYP - RACE, data = nhanes_df)
#>
#> Call:
#> lm(formula = SBP ~ . - ID - RACE - EDUCATION - INCOME - SMOKE -
#>      YEAR - BMI_CAT - LEAD_QUANTILE - DBP - ALC - HYP - RACE,
#>      data = nhanes_df)
#>
#> Coefficients:
#> (Intercept)          AGE       SEXMale        LEAD
#>     99.008        0.462        2.778        0.400

```

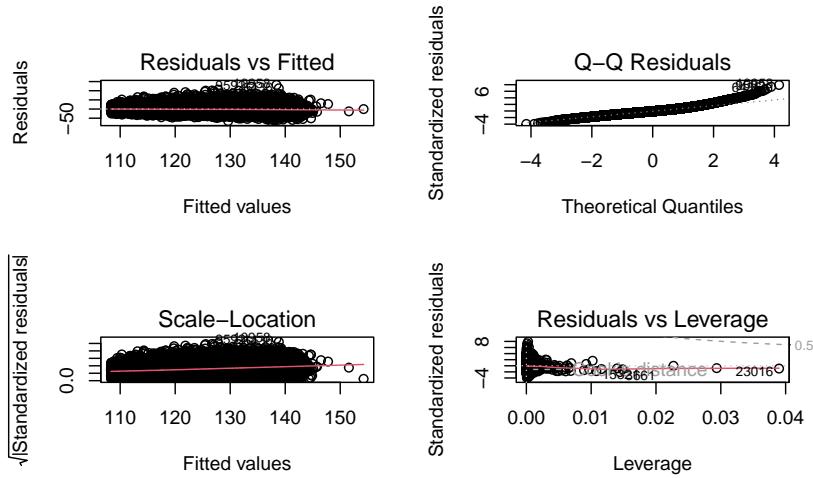
## 10.3 Diagnostic Plots and Measures

We can tell from the above plot that our model doesn't have a great fit. We will use some further diagnostic plots and measures to learn more. R has some built-in plots available for linear regression models, which can be displayed using the `plot()` function. Similar to the `summary()` function, this function acts differently when passed an `lm` object. The four plots include (a) Residuals vs. Fitted, (b) a QQ-plot for the residuals, (c) Standardized residuals (sqrt) vs. Fitted, and (d) Standardized Residuals vs. Leverage. In the last plot, you may observe that there is a dashed line. Any points outside of these lines have a Cook's distance of greater than 0.5. Additionally, points with labels correspond to the points with the largest residuals, so this last plot summarizes the outliers, leverage, and influential points. The plots below show that our residuals do not look normally distributed and that we may have some high leverage points.

```

par(mfrow=c(2,2)) # plots all four plots together
plot(adj_model)

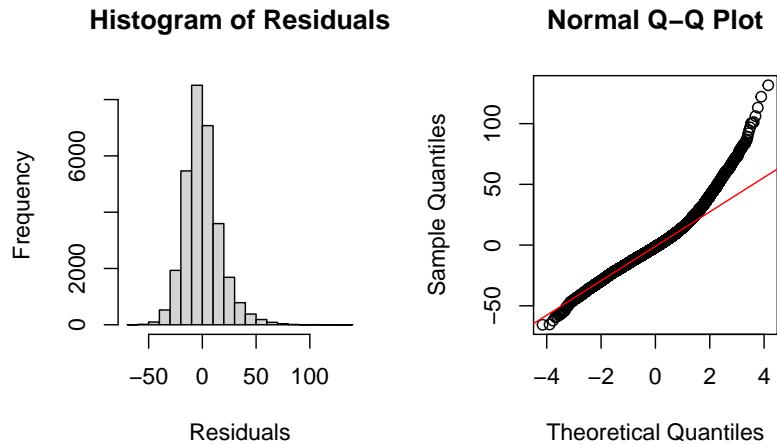
```



### 10.3.1 Normality

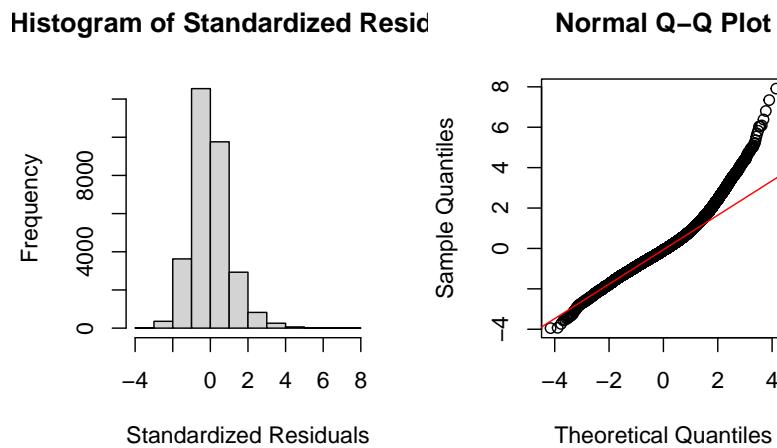
Beyond the default plots, we can also plot a histogram of the residuals and a qq-plot. The `qqnorm()` and `qqline()` functions can take in the residuals from our model as an argument. The latter adds the theoretical red line for reference. As both the histogram and qq-plot shown, the residuals are positively skewed, and thus the assumption of normality is not satisfied for our residuals. Later in this chapter, we will discuss how we might transform this dataset and/or model to satisfy this assumption.

```
par(mfrow=c(1,2)) # plot next to each other
hist(resid(adj_model), xlab="Residuals", main="Histogram of Residuals")
qqnorm(resid(adj_model))
qqline(resid(adj_model), col="red")
```



Instead of using the direct residuals, we can create the plots above using the standardized residuals with the function `rstandard()`. The standardized residuals are the raw residuals divided by an estimate of the standard deviation for the residual, which will be different for each observation.

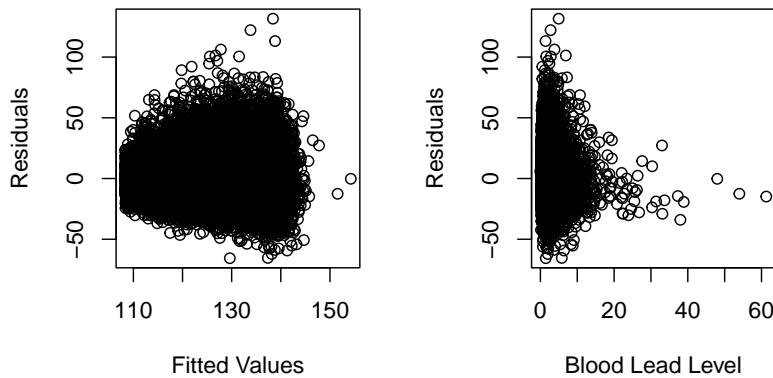
```
par(mfrow=c(1,2))
hist(rstandard(adj_model), xlab="Standardized Residuals",
      main="Histogram of Standardized Residuals")
qqnorm(rstandard(adj_model))
qqline(rstandard(adj_model), col="red")
```



### 10.3.2 Homoscedasticity, Linearity, and Collinearity

We can also create a residual vs. fitted plot or plot the residuals against included covariates. Below, we plot the blood lead level against the residuals. In both plots, we are looking for the points to be spread roughly evenly around 0 with no discerning pattern. However, both plots shows a tunnel shape, indicating a growing and shrinking variance of residuals by level, respectively. This indicates that we are violating the homoscedasticity assumption.

```
par(mfrow=c(1,2))
plot(fitted(adj_model), resid(adj_model), xlab="Fitted Values", ylab="Residuals")
plot(nhanes_df$LEAD, resid(adj_model), xlab="Blood Lead Level", ylab="Residuals")
```



To quantify any collinearity between the included covariates, we can calculate the variance inflation factors. The `vif()` function in the `car` package allows us to calculate the variance inflation factors or generalized variance inflation factors for all covariates. In our case, all the VIF values are around 1, indicating low levels of collinearity.

```
vif(adj_model)
#> LEAD   AGE   SEX
#> 1.12  1.07  1.05
```

### 10.3.3 Practice Question

Fit a linear regression model with SBP as the outcome and with INCOME, RACE, EDUCATION, and ALC as independent variables. Then, plot the residuals vs. the fitted values as well and make

a QQ plot for the standardized residuals from this model. They should look like this:

```
# Insert your solution here:
```

#### 10.3.4 Leverage and Influence

We may also be interested in how each observation is influencing the model. Leverage values measure how much an individual observation's  $y$  value influences its own predicted value and indicate whether observations have extreme predictor values compared to the rest of the data. Leverage values range from 0 to 1 and sum to the number of estimated coefficients. Observations with high leverage have the potential to significantly impact the estimated regression coefficients and the overall fit of the model. Therefore, examining leverage values helps identify observations that may be influential or outliers. Below we find the ten highest leverage values and then find those observations in the data.

```
sort(hatvalues(adj_model), decreasing=TRUE)[1:10]
#> 23016   2511   3091   21891   3661    511   21892   15321   6511
#> 0.03899 0.02936 0.02270 0.01484 0.01443 0.01399 0.01159 0.01080 0.01022
#> 3452
#> 0.00968
nhanes_df[order(hatvalues(adj_model), decreasing=TRUE),] %>%
  select(c(SBP, LEAD, AGE, SEX)) %>% head(10)
#>      SBP LEAD AGE  SEX
#> 23016 129 61.3 38 Male
#> 2511  139 54.0 61 Male
#> 3091  154 48.0 72 Male
#> 21891 123 38.9 54 Male
#> 3661  101 38.0 39 Male
#> 511   118 37.3 34 Male
#> 21892 107 33.7 21 Male
#> 15321 104 33.1 39 Male
#> 6511  175 33.0 71 Male
#> 3452  113 31.4 38 Male
```

Some other measures of influence are the DFBETAs and Cook's distance, which measure how much each observation influences the estimated coefficients and the estimated  $y$  values, respectively. The `influence.measures()` function provides a set of measures that quantify the influence of each observation on a linear regression model: these include the DFBETAS for each model variable, DFFITS, covariance ratios, Cook's distances, and the leverage values. The output returns the values in a matrix called `infmt`, which we convert to a data frame below.

```

inf_mat <- influence.measures(adj_model)[['infmt']]
as.data.frame(inf_mat) %>% head()
#>      dfb.1_  dfb.LEAD  dfb.AGE  dfb.SEXF    dffit cov.r   cook.d
#> 1  0.013880 -0.017564 -1.68e-02  0.008319 -0.03427 1.000 2.93e-04
#> 2 -0.000732  0.000348 -3.92e-05  0.001051 -0.00150 1.000 5.59e-07
#> 3  0.022137  0.005749 -1.45e-02 -0.016843  0.02964 0.999 2.19e-04
#> 4  0.000499  0.001043 -2.07e-03  0.001631 -0.00312 1.000 2.43e-06
#> 5  0.002259 -0.002725 -2.50e-03  0.000973 -0.00498 1.000 6.20e-06
#> 6 -0.001283 -0.000559  1.65e-03 -0.002929 -0.00441 1.000 4.87e-06
#>      hat
#> 1 1.90e-04
#> 2 6.61e-05
#> 3 8.28e-05
#> 4 1.18e-04
#> 5 2.35e-04
#> 6 8.09e-05

```

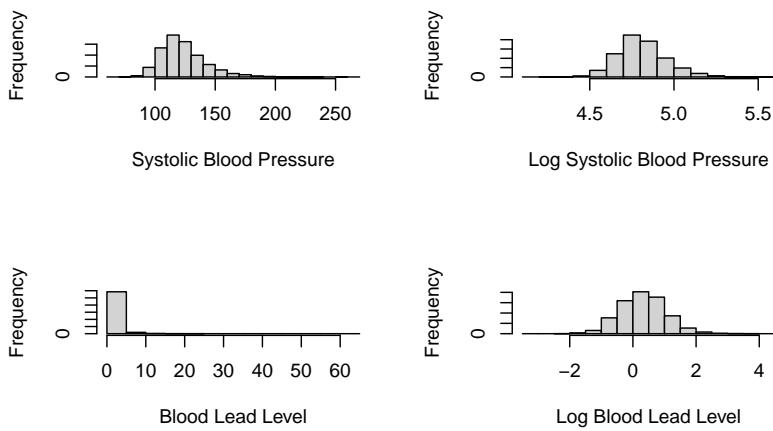
## 10.4 Interactions and Transformations

We now try to improve our model. To start, we look at potential transformations for our outcome variable. We will consider a log transformation for both our outcome, systolic blood pressure, and our predictor of interest, blood lead level. Both of these variables have a fairly skewed distribution and may benefit from such a transformation. Below, you can see that the transformed variables have distributions that are more symmetrical.

```

par(mfrow=c(2,2))
hist(nhanes_df$SBP, xlab="Systolic Blood Pressure", main="")
hist(log(nhanes_df$SBP), xlab="Log Systolic Blood Pressure", main="")
hist(nhanes_df$LEAD, xlab="Blood Lead Level", main="")
hist(log(nhanes_df$LEAD), xlab="Log Blood Lead Level", main="")

```



To add a transformation to a model, we can simply apply the transformation in the formula for `lm()`. We will calculate the adjusted R-squared for each potential model to compare their fits in addition to plotting the four qq-plots. Both indicate that the model with the log-log transformation (that is, with a log transformation applied to both the SBP and the LEAD variables) is the best fit though the model with just a log transformation for SBP has a similar qq-plot.

```

model_nlog_nlog <- lm(SBP ~ LEAD + AGE + SEX, data = nhanes_df)
model_log_nlog <- lm(log(SBP) ~ LEAD + AGE + SEX, data = nhanes_df)
model_nlog_log <- lm(SBP ~ log(LEAD) + AGE + SEX, data = nhanes_df)
model_log_log <- lm(log(SBP) ~ log(LEAD) + AGE + SEX, data = nhanes_df)

summary(model_nlog_nlog)$adj.r.squared
#> [1] 0.212
summary(model_log_nlog)$adj.r.squared
#> [1] 0.215
summary(model_nlog_log)$adj.r.squared
#> [1] 0.212
summary(model_log_log)$adj.r.squared
#> [1] 0.215

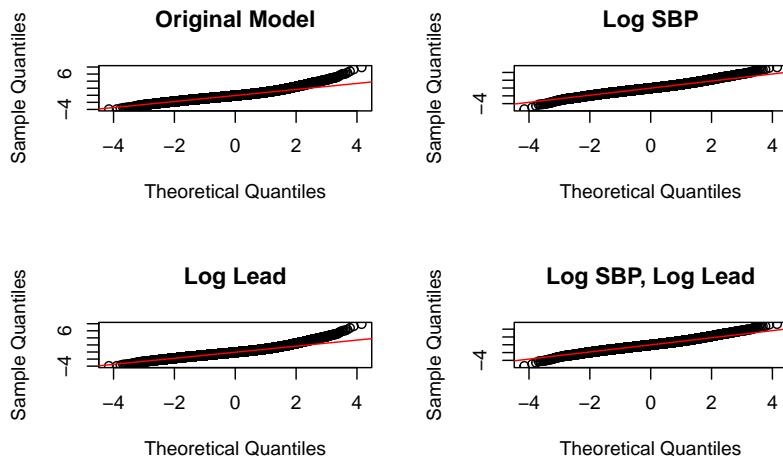
par(mfrow=c(2,2))
qqnorm(rstandard(model_nlog_nlog), main="Original Model")
qqline(rstandard(model_nlog_nlog), col="red")
qqnorm(rstandard(model_log_nlog), main="Log SBP")

```

```

qqline(rstandard(model_log_nlog), col="red")
qqnorm(rstandard(model_nlog_log), main="Log Lead")
qqline(rstandard(model_nlog_log), col="red")
qnnorm(rstandard(model_log_log), main="Log SBP, Log Lead")
qqline(rstandard(model_log_log), col="red")

```



#### 10.4.1 Practice Question

Instead of adding in a log transformation for LEAD like we did above, try a square root transformation `sqrt(LEAD)` and an inverse transformation `1/LEAD` while keeping the log transformation for the outcome `log(SBP)`. Which model fits better according to the adjusted R-squared? The resulting QQ plots should look like this:

```
# Insert your solution here:
```

Additionally, we might consider polynomial transformations. The `poly(x, degree=1)` function allows us to specify a polynomial transformation where we might have higher degree terms. We do not pursue this for this particular example, but we show some example code below for creating such a transformation (in this case, a cubic transformation for blood lead level).

```
model_poly <- lm(SBP ~ poly(LEAD, 3) + AGE + SEX, data = nhanes_df)
```

We can summarize the outcome for our log-log model using the `tidy()` function again. We observe small p-values for each estimated coefficient.

```

tidy(model_log_log)
#> # A tibble: 4 x 5
#>   term      estimate std.error statistic p.value
#>   <chr>     <dbl>     <dbl>     <dbl>    <dbl>
#> 1 (Intercept)  4.62     0.00239    1932.     0
#> 2 log(LEAD)    0.00891   0.00118     7.53 5.34e-14
#> 3 AGE         0.00349   0.0000457    76.4    0
#> 4 SEXMale     0.0254    0.00155     16.4  2.06e-60

```

Another component that we may want to add to our model is an interaction term. For example, we may consider an interaction between sex and blood lead level. We add an interaction to the formula using a : between the two variables. The output below shows that the coefficient for this interaction is indeed significant.

```

model_interaction <- lm(log(SBP) ~ log(LEAD) + AGE + SEX + SEX:log(LEAD),
                        data=nhanes_df)
summary(model_interaction)
#>
#> Call:
#> lm(formula = log(SBP) ~ log(LEAD) + AGE + SEX + SEX:log(LEAD),
#>      data = nhanes_df)
#>
#> Residuals:
#>   Min     1Q Median     3Q    Max
#> -0.6981 -0.0816 -0.0049  0.0752  0.6599
#>
#> Coefficients:
#>              Estimate Std. Error t value Pr(>|t|)
#> (Intercept) 4.62e+00  2.39e-03 1936.2  <2e-16 ***
#> log(LEAD)   2.36e-02  1.68e-03   14.1  <2e-16 ***
#> AGE        3.45e-03  4.58e-05   75.3  <2e-16 ***
#> SEXMale    3.32e-02  1.67e-03   19.9  <2e-16 ***
#> log(LEAD):SEXMale -2.66e-02  2.16e-03  -12.3  <2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 0.128 on 30400 degrees of freedom
#> Multiple R-squared:  0.219, Adjusted R-squared:  0.219
#> F-statistic: 2.13e+03 on 4 and 30400 DF,  p-value: <2e-16

```

## 10.5 Evaluation Metrics

Besides the adjusted R-squared, there are a few other metrics that can help us to understand how well our model fits the data and to help with model selection. The `AIC()` and `BIC()` functions find the Akaike information criterion (AIC) and Bayesian information criterion (BIC) values, respectively. Both AIC and BIC balance the trade-off between model complexity and goodness of fit. AIC takes into account both the goodness of fit (captured by the likelihood of the model) and the complexity of the model (captured by the number of parameters used). Lower AIC values are preferable. BIC is similar to AIC but has a stronger penalty for model complexity compared to AIC. Both measures indicate a preference for keeping the interaction term.

```
AIC(model_log_log)
#> [1] -38610
AIC(model_interaction)
#> [1] -38760

BIC(model_log_log)
#> [1] -38569
BIC(model_interaction)
#> [1] -38710
```

The `predict()` function allows us to calculate the predicted y values. When called on a model with no data specified, it returns the predicted values for the training data. We could also specify new data using the `newdata` argument. The new data provided must contain the columns given in the model formula. Below, we use the `predict()` function to find the predicted values from our model and then calculate the mean absolute error (MAE) and mean squared error (MSE) for our model. MAE is less sensitive to outliers compared to MSE. The mean absolute error indicates that our model has fairly high residuals on average. While this model may be helpful to understand the relationship between blood lead level and systolic blood pressure, it would not be very useful as a tool to predict the latter.

```
pred_y <- predict(model_interaction)

mae <- mean(abs(nhanes_df$SBP - pred_y))
mae
#> [1] 119

mse <- mean((nhanes_df$SBP - pred_y)^2)
mse
```

```
#> [1] 14502
```

## 10.6 Stepwise Selection

So far we have ignored the other variables in the data frame. When performing variable selection, there are multiple methods to use. We will end this chapter by demonstrating how to implement one such method, **stepwise selection**, in R. The `step()` function takes in an initial model to perform stepwise selection on along with a direction `direction` ("forward", "backward", or "both"), and a scope `scope`. The scope specifies the lower and upper model formulas to consider. Below, we use forward selection so the lower formula is the formula for our current model and the upper formula contains the other covariates we are considering adding in. These two formulas must be nested - that is, all terms in the lower formula must be contained in the upper formula.

By default, the `step()` function prints each step in the process and uses AIC to guide its decisions. We can set `trace=0` to avoid the print behavior and update the argument `k` to `log(n)` to use BIC, where `n` is the number of observations. Below we see that the algorithm first adds in race, then BMI, then income, then education, and then smoking status. In fact, all variables were added to the model! The final output is an `lm` object that we can use just like the ones earlier in this chapter. We get the summary of the final model and see that the adjusted R-squared has improved to 0.2479.

```
mod_step <- step(model_interaction, direction = 'forward',
                   scope = list(lower = "log(SBP) ~ log(LEAD) + AGE + SEX:log(LEAD)",
                               upper = "log(SBP) ~ log(LEAD) + AGE + SEX:log(LEAD) +
                                         SEX + RACE + EDUCATION + SMOKE + INCOME + BMI_CAT"))

#> Start:  AIC=-125048
#> log(SBP) ~ log(LEAD) + AGE + SEX + SEX:log(LEAD)
#>
#>          Df Sum of Sq RSS      AIC
#> + RACE     4    9.16 488 -125605
#> + BMI_CAT  2    8.97 488 -125597
#> + INCOME   1    2.87 494 -125222
#> + EDUCATION 2    1.90 495 -125160
#> + SMOKE    2    0.35 497 -125065
#> <none>           497 -125048
#>
#> Step:  AIC=-125605
#> log(SBP) ~ log(LEAD) + AGE + SEX + RACE + log(LEAD):SEX
#>
```

```

#>          Df Sum of Sq RSS      AIC
#> + BMI_CAT    2     7.16 481 -126050
#> + INCOME     1     1.80 486 -125715
#> + EDUCATION   2     1.34 487 -125684
#> + SMOKE      2     0.13 488 -125609
#> <none>           488 -125605
#>
#> Step: AIC=-126050
#> log(SBP) ~ log(LEAD) + AGE + SEX + RACE + BMI_CAT + log(LEAD):SEX
#>
#>          Df Sum of Sq RSS      AIC
#> + INCOME     1     1.617 479 -126151
#> + EDUCATION   2     1.112 480 -126117
#> + SMOKE      2     0.261 481 -126063
#> <none>           481 -126050
#>
#> Step: AIC=-126151
#> log(SBP) ~ log(LEAD) + AGE + SEX + RACE + BMI_CAT + INCOME +
#>     log(LEAD):SEX
#>
#>          Df Sum of Sq RSS      AIC
#> + EDUCATION   2     0.418 479 -126173
#> + SMOKE      2     0.258 479 -126163
#> <none>           479 -126151
#>
#> Step: AIC=-126173
#> log(SBP) ~ log(LEAD) + AGE + SEX + RACE + BMI_CAT + INCOME +
#>     EDUCATION + log(LEAD):SEX
#>
#>          Df Sum of Sq RSS      AIC
#> + SMOKE     2     0.286 479 -126187
#> <none>           479 -126173
#>
#> Step: AIC=-126187
#> log(SBP) ~ log(LEAD) + AGE + SEX + RACE + BMI_CAT + INCOME +
#>     EDUCATION + SMOKE + log(LEAD):SEX

summary(mod_step)
#>
#> Call:
#> lm(formula = log(SBP) ~ log(LEAD) + AGE + SEX + RACE + BMI_CAT +

```

```

#>      INCOME + EDUCATION + SMOKE + log(LEAD):SEX, data = nhanes_df)
#>
#> Residuals:
#>    Min     1Q Median     3Q    Max
#> -0.6713 -0.0799 -0.0039  0.0738  0.6797
#>
#> Coefficients:
#>                               Estimate Std. Error t value Pr(>|t|)
#> (Intercept)                 4.61e+00  3.32e-03 1391.51 < 2e-16 ***
#> log(LEAD)                   2.28e-02  1.69e-03   13.47 < 2e-16 ***
#> AGE                         3.48e-03  4.85e-05   71.87 < 2e-16 ***
#> SEXMale                      3.47e-02  1.65e-03   20.94 < 2e-16 ***
#> RACEOther Hispanic          -7.11e-03  3.22e-03   -2.20   0.027 *
#> RACENon-Hispanic White     -4.45e-03  2.20e-03   -2.02   0.043 *
#> RACENon-Hispanic Black     3.37e-02  2.47e-03   13.66 < 2e-16 ***
#> RACEOther Race              6.27e-03  3.39e-03    1.85   0.064 .
#> BMI_CAT25<BMI<30          1.51e-02  1.84e-03    8.23 < 2e-16 ***
#> BMI_CATBMI>=30             3.78e-02  1.83e-03   20.62 < 2e-16 ***
#> INCOME                       -3.89e-03  5.00e-04   -7.78  7.6e-15 ***
#> EDUCATIONHS                  -1.94e-05  2.19e-03   -0.01   0.993
#> EDUCATIONMoreThanHS         -8.69e-03  2.07e-03   -4.20  2.6e-05 ***
#> SMOKEQuitSmoke               -7.56e-03  1.80e-03   -4.21  2.6e-05 ***
#> SMOKEStillSmoke              -4.04e-03  1.94e-03   -2.08   0.038 *
#> log(LEAD):SEXMale            -2.61e-02  2.12e-03  -12.28 < 2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 0.126 on 30389 degrees of freedom
#> Multiple R-squared:  0.248, Adjusted R-squared:  0.248
#> F-statistic:  669 on 15 and 30389 DF, p-value: <2e-16

```

## 10.7 Recap Video

<https://www.youtube.com/embed/l4efC80vElw>

## 10.8 Exercises

For these exercises, we will continue using the `nhanes_df` data.

1. Construct a linear model using DBP as the output and LEAD, AGE, and EVER\_SMOKE as features, and print the output.
2. Use forward stepwise selection to add possible interactions to the linear model from the previous question.
3. Draw a QQ plot for the model in Question 2, and describe the distribution that you observe.
4. Report the MAE and MSE of the model developed in Question 2. Then, find the row numbers of the observations with the top 5 Cook's Distance values for this model.
5. Look at some diagnostic plots for the model and use what you observe from these plots to choose a transformation that will improve the fit of this model. Then, fit and summarize this new model with the transformation included. How do the MSE and MAE of the new model compare to the previous one? Note that your predictions will be on the transformed scale so you'll need to convert them to the correct scale.

# 11 Logistic Regression

This chapter will build on the last and continue with regression analysis in R. Specifically, we will cover binary logistic regression using the `glm()` function, which can be used to fit generalized linear models. Many of the functions learned in the last chapter can also be used with a `glm` object. For example, the `glm()` function expects a formula in the same way as the `lm()` function. We will also cover diagnostic plots and model evaluation specific to a binary outcome.

The data used in this chapter is from the 2021 National Youth Tobacco Survey (NYTS). This dataset contains 20,413 participants and a set of variables relating to demographic information, frequency of tobacco use, and methods of obtaining said tobacco as reported by students on the 2021 NYTS. We will use logistic regression to examine whether survey setting was associated with youth reporting of current tobacco use similar to the analysis presented in [Park-Lee et al. \(2023\). Impact of Survey Setting on Current Tobacco Product Use: National Youth Tobacco Survey, 2021. Journal of Adolescent Health, 72\(3\), 365-374](#). Note that we ignore survey weights for this analysis.

We will use the `broom` package again to present the estimated coefficients, the `tidyverse` package to create a calibration plots, the `lmtree` package to perform likelihood ratio tests, and the `pROC` package to create receiver operating characteristic curves.

```
suppressPackageStartupMessages(library(broom))
suppressPackageStartupMessages(library(tidyverse))
suppressPackageStartupMessages(library(pROC))
suppressPackageStartupMessages(library(lmtest))
library(HDSinRdata)
data(nyts)
```

## 11.1 Generalized Linear Models in R

The `glm(formula, data, family)` function in R is used to fit generalized linear models. The three main arguments we must specify to the function are the

- **formula** - specifies the relationship between the independent variables and the outcome of interest,
- **data** - the dataset used to train the model, and
- **family** - a description of the error distribution and link function to be used in the model.

In binary logistic regression, we assume a binomial outcome and use the logit link function. We can specify this by setting `family = binomial`. By default, this will assume the link function is the logit function. Note that we can even use the `glm()` function to implement linear regression by setting `family = gaussian`. Using our example from [Chapter 10](#), running `glm(SBP~LEAD, data = nhanes_df, family= gaussian)` would be equivalent to `lm(SBP~LEAD, data = nhanes_df)`.

Our outcome of interest will be current e-cigarette use, `e_cig_use`, so we need to create this variable from the variables that are currently in the data. We set `e_cig_use` to 0 if the respondent answered that they have not used e-cigarettes in the last 30 days and 1 otherwise. We can see that there are only 1,435 respondents who reported e-cigarette use. This is a low percentage of the overall sample, which will likely impact our results.

```
nyts$e_cig_use <- as.factor(ifelse(nyts$num_e_cigs==0, "0", "1"))
table(nyts$e_cig_use)
#>
#>     0      1
#> 18683 1435
```

Looking at the covariate of interest, survey setting, we can see that there are 85 respondents that took the survey in “Some other place”. Since we are interested in the impact of taking the survey at school compared to other settings, we will simplify this variable to have two levels: “school” and “home/other”.

```
table(nyts$location)
#>
#> At home (virtual learning) In a school building/classroom
#>                               8738                           10737
#> Some other place
#>                               85
nyts$location <- ifelse(nyts$location == "In a school building/classroom",
                        "school", "home/other")
nyts$location <- as.factor(nyts$location)
```

To start, we will create a model to predict e-cigarette use from school setting adjusting for the covariates sex, school level, and race and ethnicity. Note that we specify our formula and data

as with the `lm()` function. We then use the `summary()` function again to print a summary of this fitted model. The output is slightly different from an `lm` object. We can see the null and residual deviances are reported along with the AIC. Adding transformations and interactions is equivalent to that in the `lm()` function and is not demonstrated in this chapter.

```
mod_start <- glm(e_cig_use ~ grade + sex + race_and_ethnicity + location,
                  data = nyts, family = binomial)
summary(mod_start)

#>
#> Call:
#> glm(formula = e_cig_use ~ grade + sex + race_and_ethnicity +
#>     location, family = binomial, data = nyts)
#>
#> Coefficients:
#>
#> (Intercept)           -4.6017    0.1539   -29.91
#> grade7th              0.4461    0.1753    2.54
#> grade8th              0.9677    0.1607    6.02
#> grade9th              1.3830    0.1549    8.93
#> grade10th             1.9183    0.1513   12.68
#> grade11th             2.1385    0.1491   14.34
#> grade12th             2.4286    0.1492   16.28
#> gradeUngraded or Other Grade 2.5213    0.4487    5.62
#> sexFemale              0.1922    0.0580    3.32
#> race_and_ethnicitynon-Hispanic Black -0.6614    0.1121   -5.90
#> race_and_ethnicitynon-Hispanic other race -0.1021    0.1515   -0.67
#> race_and_ethnicitynon-Hispanic White    0.1983    0.0739    2.68
#> locationschool          0.7223    0.0648   11.14
#> Pr(>|z|)
#> (Intercept)            < 2e-16 ***
#> grade7th                0.01095 *
#> grade8th                1.7e-09 ***
#> grade9th                < 2e-16 ***
#> grade10th               < 2e-16 ***
#> grade11th               < 2e-16 ***
#> grade12th               < 2e-16 ***
#> gradeUngraded or Other Grade 1.9e-08 ***
#> sexFemale                0.00091 ***
#> race_and_ethnicitynon-Hispanic Black 3.6e-09 ***
#> race_and_ethnicitynon-Hispanic other race 0.50061
#> race_and_ethnicitynon-Hispanic White    0.00726 **
#> locationschool            < 2e-16 ***
```

```

#> ---
#> Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> (Dispersion parameter for binomial family taken to be 1)
#>
#> Null deviance: 9754.9 on 18746 degrees of freedom
#> Residual deviance: 8886.8 on 18734 degrees of freedom
#> (1666 observations deleted due to missingness)
#> AIC: 8913
#>
#> Number of Fisher Scoring iterations: 6

```

We can use the `tidy()` function from the `broom` package to display the estimated coefficients from the above model. This time we add the `exponentiate = TRUE` argument to exponentiate our coefficients so we can interpret them as estimated change in odds rather than log odds. For example, we can see below that those who answered at school have double the estimated odds of reporting e-cigarette use compared to those who took the survey at home/other, adjusting for grade, sex, and race and ethnicity.

```

tidy(mod_start, exponentiate=TRUE)
#> # A tibble: 13 x 5
#>   term      estimate std.error statistic  p.value
#>   <chr>     <dbl>    <dbl>     <dbl>    <dbl>
#> 1 (Intercept) 0.0100    0.154    -29.9  1.68e-196
#> 2 grade7th    1.56      0.175     2.54  1.10e- 2
#> 3 grade8th    2.63      0.161     6.02  1.73e- 9
#> 4 grade9th    3.99      0.155     8.93  4.41e-19
#> 5 grade10th   6.81      0.151    12.7   7.94e-37
#> # i 8 more rows

```

### 11.1.1 Practice Question

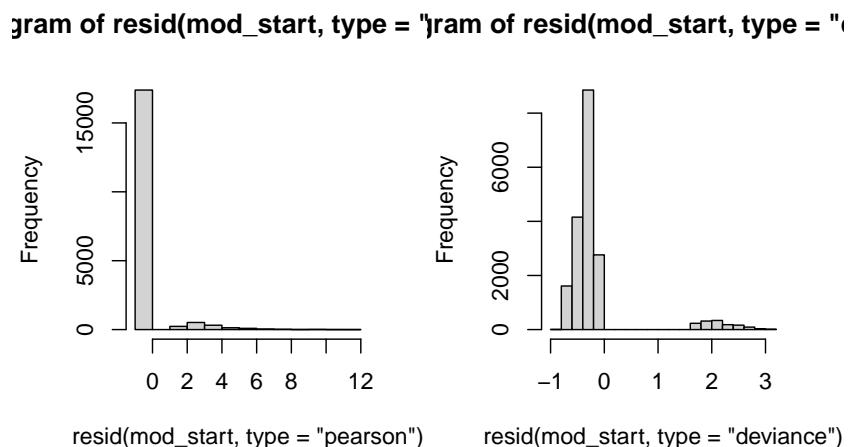
Fit a logistic regression model with cigarette use as the outcome and age, race\_and\_ethnicity, LGBT, and family\_affluence as well as an interaction between family\_affluence and race\_and\_ethnicity as independent variables. Your AIC should be 2430.8.

```
# Insert your solution here:
```

## 11.2 Residuals, Discrimination, and Calibration

Next, we look at the distribution of the residuals. The `resid()` function can be used to find the residuals again, but this time we might want to specify the Pearson and deviance residuals by specifying the `type` argument. We plot histograms for both of these residual types below. In both plots, we can observe a multi-modal distribution, which reflects the binary nature of our outcome.

```
par(mfrow=c(1,2))
hist(resid(mod_start, type="pearson"))
hist(resid(mod_start, type="deviance"))
```

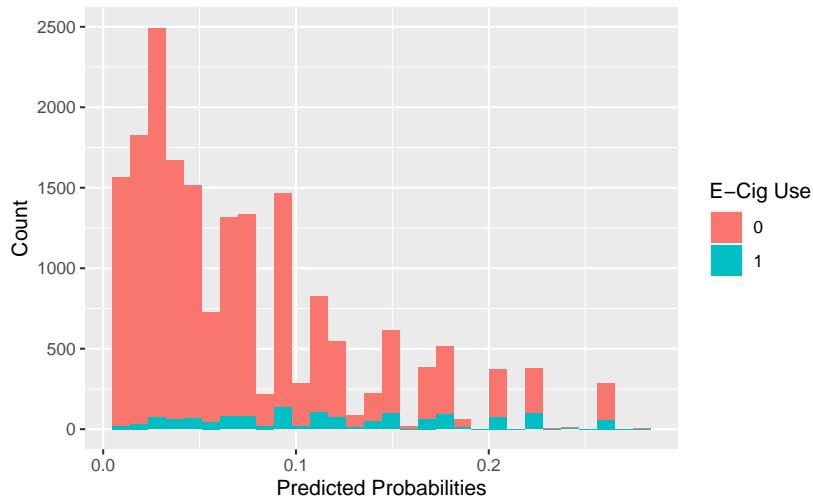


To further evaluate the fit of our model, we may want to observe the predicted probabilities. The `predict()` function by default will return the predicted value on the scale of the linear predictors. In this case, that is the predicted log odds. If want to find the predicted probabilities, we can update the argument by specifying `type="response"`. Additionally, we can predict on data not used to train the model by using the argument `newdata`. Note that there are only 18,747 predicted probabilities despite our training data having more observations. This is because the `glm()` function (and `lm()` function) drop any observations with NA values when training. In the last chapter, we omitted incomplete cases prior to analysis so that the predicted probabilities corresponded directly to the rows in our data.

```
pred_probs <- predict(mod_start, type="response")
length(pred_probs)
#> [1] 18747
```

If we want to find the class for each observation used in fitting the model, we can use the model's output, which stores the model matrix `x` and the outcome vector `y`. We plot the distribution of estimated probabilities for each class. Note that all the predicted probabilities are below 0.5, the typical cut-off for prediction. This is in part due to the fact that we have such an imbalanced outcome.

```
ggplot() +
  geom_histogram(aes(x=pred_probs, fill=as.factor(mod_start$y)),
                 bins=30) +
  scale_fill_discrete(name="E-Cig Use") +
  labs(x="Predicted Probabilities", y="Count")
```



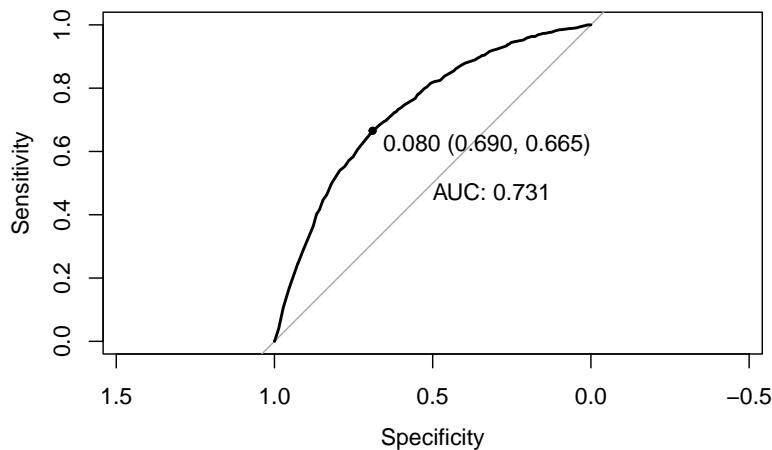
### 11.2.1 Receiver Operating Characteristic (ROC) Curve

We now plot the receiver operating characteristic (ROC) curve and compute the area under the curve (AUC). The `roc()` function from the `pROC` package builds an ROC curve. The function has several ways to specify a response and predictor. For example, we can specify the response vector `response` and predictor vector `predictor`. By default, with a 0/1 outcome, the `roc()` function will assume class 0 is controls and class 1 is cases. We can also specify this in the `levels` argument to specify the value of the response for controls and cases, respectively. Additionally, the function assumes the predictor vector specifies predicted probabilities for the class 1. We can change the argument `direction = ">"` if the opposite is true. We can plot the ROC curve by calling the `plot()` function. We can add some extra information by adding the AUC (`print.auc = TRUE`) and the threshold that maximizes sensitivity + specificity (`print.thres = TRUE`).

```

roc_mod <- roc(predictor=pred_probs,
                 response=as.factor(mod_start$y),
                 levels = c(0,1), direction = "<")
plot(roc_mod, print.auc=TRUE, print.thres = TRUE)

```



If we want to understand more about the curve, we can use the `coords()` function to find the coordinates for each threshold used to create the curve. The argument `x= "all"` specifies we want to find all thresholds, but we could also specify only to return local maxima.

```

roc_vals <- coords(roc=roc_mod, x = "all")
head(roc_vals)
#>   threshold specificity sensitivity
#> 1      -Inf     0.00000     1.000
#> 2     0.00569     0.00523     1.000
#> 3     0.00713     0.01070     1.000
#> 4     0.00850     0.01547     0.999
#> 5     0.00934     0.01835     0.998
#> 6     0.00982     0.02404     0.996

```

For example, we could use this information to find the highest threshold with a corresponding sensitivity above 0.75. This returns a threshold of 0.062. If we were to predict class 1 for all observations with a predicted probability above 0.062, then we would achieve a sensitivity of 0.77 and specificity of 0.56 on the training data.

```

roc_vals[roc_vals$sensitivity > 0.75, ] %>% tail(n=1)
#>   threshold specificity sensitivity
#> 63      0.062      0.555      0.768

```

We will use the threshold of 0.080 indicated on our ROC curve to create predicted classes for our response. By comparing the result to our outcome using the `table()` function, we can directly calculate measures like sensitivity, specificity, positive and negative predictive values, and overall accuracy.

```

pred_ys <- ifelse(pred_probs > 0.08, 1, 0)
tab_outcome <- table(mod_start$y, pred_ys)
tab_outcome
#>   pred_ys
#>     0     1
#> 0 11992  5395
#> 1    455   905

sens <- tab_outcome[2,2]/(tab_outcome[2,1]+tab_outcome[2,2])
spec <- tab_outcome[1,1]/(tab_outcome[1,1]+tab_outcome[1,2])
ppv <- tab_outcome[2,2]/(tab_outcome[1,2]+tab_outcome[2,2])
npv <- tab_outcome[1,1]/(tab_outcome[1,1]+tab_outcome[2,1])
acc <- (tab_outcome[1,1]+tab_outcome[2,2])/sum(tab_outcome)

data.frame(Measures = c("Sens", "Spec", "PPV", "NPV", "Acc"),
           Values = round(c(sens, spec, ppv, npv, acc),3))
#>   Measures Values
#> 1      Sens  0.665
#> 2      Spec  0.690
#> 3      PPV   0.144
#> 4      NPV   0.963
#> 5      Acc   0.688

```

### 11.2.2 Calibration Plot

Another useful plot is a calibration plot. This type of plot groups the data by the estimated probabilities and compares the mean probability with the observed proportion of observations in class 1. It visualizes how close our estimated distribution and true distribution are to each other. There are several packages that can create calibration plots, but we demonstrate how to do this using the `ggplot2` package. First, we create a data frame with the predicted probabilities and the outcome variable. Additionally, we group this data into `num_cuts` groups

based on the predicted probabilities using the `cut()` function. Within each group, we find the model's predicted mean along with the observed proportion and estimated standard errors.

```

num_cuts <- 10
calib_data <- data.frame(prob = pred_probs,
                           bin = cut(pred_probs, breaks = num_cuts),
                           class = mod_start$y)
calib_data <- calib_data %>%
  group_by(bin) %>%
  summarize(observed = sum(class)/n(),
            expected = sum(prob)/n(),
            se = sqrt(observed*(1-observed)/n()))
calib_data
#> # A tibble: 10 x 4
#>   bin           observed  expected      se
#>   <fct>        <dbl>    <dbl>    <dbl>
#> 1 (0.00488,0.0322] 0.0212  0.0203  0.00188
#> 2 (0.0322,0.0592]  0.0440  0.0441  0.00328
#> 3 (0.0592,0.0862] 0.0621  0.0708  0.00451
#> 4 (0.0862,0.113]  0.0986  0.0988  0.00587
#> 5 (0.113,0.14]    0.131   0.123   0.0131
#> # i 5 more rows

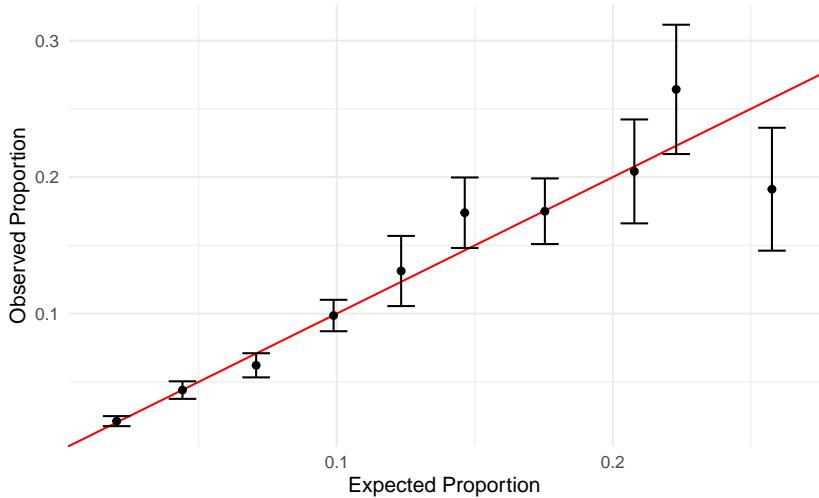
```

Next, we plot the observed vs expected proportions. We also used the estimated standard error to create corresponding 95% confidence intervals. The red line indicates a perfect fit where our estimated and true distributions match. Overall, the plot below shows that our model could be better calibrated.

```

ggplot(calib_data) +
  geom_abline(intercept = 0, slope = 1, color="red") +
  geom_errorbar(aes(x = expected, ymin=observed-1.96*se,
                     ymax=observed+1.96*se),
                 colour="black", width=.01) +
  geom_point(aes(x = expected, y = observed)) +
  labs(x="Expected Proportion", y="Observed Proportion") +
  theme_minimal()

```



### 11.2.3 Practice Question

Create a calibration plot with 5 cuts for your model from the previous practice question (recall that this model should have cigarette use as the outcome and age, race\_and\_ethnicity, LGBT, and family\_affluence as well as an interaction between family\_affluence and race\_and\_ethnicity as independent variables). It should look like this:

```
# Insert your solution here:
```

## 11.3 Variable Selection and Likelihood Ratio Tests

In the last chapter, we introduced the `step()` function to implement stepwise variable selection. This function also works with `glm` objects. In this case, we use this function to implement backward selection from a larger set of covariates. We first remove any observations with NA values to ensure that our training data does not change size as the formula changes.

```
nyts_sub <- nyts %>%
  dplyr::select(location, sex, grade, otherlang, grades_in_past_year,
                perceived_e_cig_use, race_and_ethnicity, LGBT,
                psych_distress, family_affluence, e_cig_use) %>%
  na.omit()
head(nyts_sub)
#> # A tibble: 6 x 11
#>   location sex    grade otherlang grades_in_past_year perceived_e_cig_use
```

```

#> <fct> <fct> <fct> <fct> <dbl>
#> 1 school Male 6th No Mostly A's 0
#> 2 school Fema~ 6th No Mostly A's 0
#> 3 school Fema~ 6th No Mostly C's 0
#> 4 school Fema~ 6th No Mostly A's 0
#> 5 school Fema~ 6th No Mostly B's 0
#> # i 1 more row
#> # i 5 more variables: race_and_ethnicity <chr>, LGBT <chr>,
#> # psych_distress <chr>, family_affluence <chr>, e_cig_use <fct>

```

To implement backward selection, we first create a model with all the covariates included. The period . in the formula indicates that we want to include all variables. Next, we use the `step()` function. Since we are using backward selection, we only need to specify the lower formula in the scope.

```

model_full <- glm(e_cig_use ~ ., data = nyts_sub, family = binomial)
mod_step <- step(model_full, direction = 'backward',
                  scope = list(lower = "e_cig_use ~ sex + grade +
race_and_ethnicity + location"))

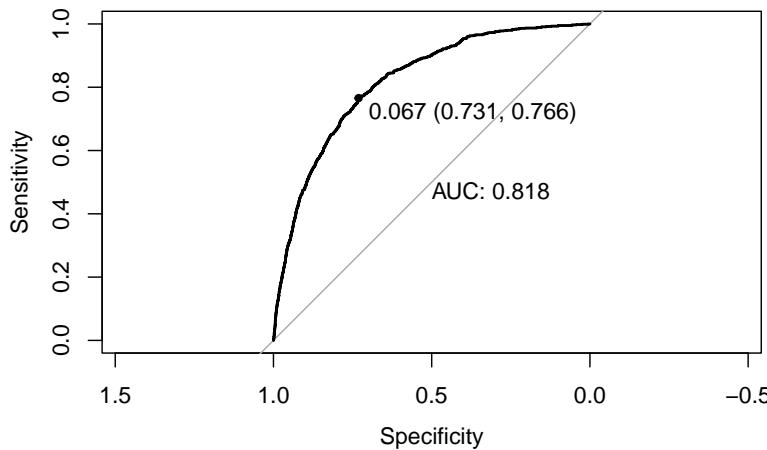
#> Start:  AIC=6093
#> e_cig_use ~ location + sex + grade + otherlang + grades_in_past_year +
#>   perceived_e_cig_use + race_and_ethnicity + LGBT + psych_distress +
#>   family_affluence
#>
#>                               Df Deviance  AIC
#> - family_affluence      2    6038 6090
#> <none>                      6037 6093
#> - otherlang              1    6042 6096
#> - LGBT                    2    6051 6103
#> - psych_distress         3    6106 6156
#> - grades_in_past_year    6    6126 6170
#> - perceived_e_cig_use    1    6416 6470
#>
#> Step:  AIC=6090
#> e_cig_use ~ location + sex + grade + otherlang + grades_in_past_year +
#>   perceived_e_cig_use + race_and_ethnicity + LGBT + psych_distress
#>
#>                               Df Deviance  AIC
#> <none>                      6038 6090
#> - otherlang                 1    6043 6093
#> - LGBT                      2    6052 6100

```

```
#> - psych_distress      3     6106 6152
#> - grades_in_past_year 6     6128 6168
#> - perceived_e_cig_use 1     6418 6468
```

Stepwise selection keeps most variables in the model and only drops family affluence. Below, we can see the AUC for this model has improved to 0.818.

```
roc_mod_step <- roc(predictor=predict(mod_step, type="response"),
                      response=as.factor(mod_step$y),
                      levels = c(0,1), direction = "<")
plot(roc_mod_step, print.auc=TRUE, print.thres = TRUE)
```



If we want to compare this model to our model above, we could use a likelihood ratio test since the two models are nested. The `lrtest()` function from the `lmeTest` package allows us to input two nested `glm` models and performs a corresponding Chi-squared likelihood ratio test. First, we need to ensure that our initial model is fit on the same data used in the stepwise selection. The output below indicates a statistically significant improvement in the model likelihood with the inclusion of the other variables.

```
mod_start2 <- glm(e_cig_use ~ grade + sex + race_and_ethnicity + location,
                    data = nyts_sub, family = binomial)

print(lrtest(mod_start2, mod_step))
#> Likelihood ratio test
#>
```

```

#> Model 1: e_cig_use ~ grade + sex + race_and_ethnicity + location
#> Model 2: e_cig_use ~ location + sex + grade + otherlang + grades_in_past_year +
#>   perceived_e_cig_use + race_and_ethnicity + LGBT + psych_distress
#> #Df LogLik Df Chisq Pr(>Chisq)
#> 1 13 -3369
#> 2 26 -3019 13    701      <2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

## 11.4 Extending Beyond Binary Outcomes

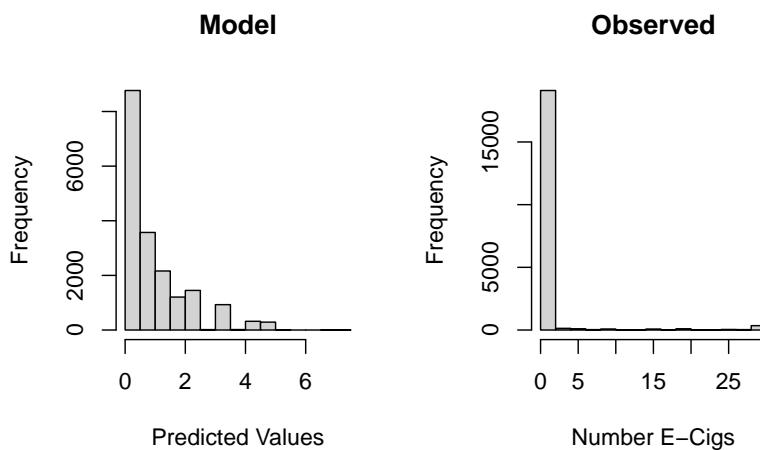
The `glm()` function can be used to fit models for other possible families and non-binary outcomes. For example, we can fit models where the outcome might follow a Poisson distribution or negative binomial distribution by updating the `family` argument. Below, we fit a Poisson model to model the number of e-cigarettes used in the last 30 days by setting `family = poisson`. However, despite the fact that our outcome is a count value, this model doesn't seem to be a good fit for our data.

```

mod_poisson <- glm(num_e_cigs ~ grade + sex + race_and_ethnicity + location,
                     data = nyts, family = poisson)

par(mfrow=c(1,2))
hist(predict(mod_poisson, type="response"), main="Model", xlab="Predicted Values")
hist(nyts$num_e_cigs, main="Observed", xlab="Number E-Cigs")

```



## 11.5 Recap Video

<https://www.youtube.com/embed/0D8Nul44eYQ>

## 11.6 Exercises

1. Create a new variable `tobacco_use` representing any tobacco use in the past 30 days (including e-cigs, cigarettes, and/or cigars) as well as a new variable `perceived_tobacco_use` equal to the maximum of the perceived cigarette and e-cig use. Then, create a new data frame `nyts_sub` that contains these two new columns as well as columns for sex, grades in the past year, psych distress, and family affluence. Finally, fit a logistic regression model with this new tobacco use variable as the outcome and all other selected variables as independent variables.
2. Perform stepwise selection on your model from Question 1 with `direction = "both"`, setting the upper scope of the model selection procedure to be a model including all two-way interactions and the lower scope to be a model including only an intercept. To specify all possible interactions you can use the formula "`tobacco_use ~ .^2`". Use the `tidy()` function to display the exponentiated estimated coefficients for the resulting model along with a confidence interval.
3. According to your model from Question 2, what is the estimated probability of tobacco use for a girl with mostly C's, moderate psych distress, and a perceived tobacco use of 0.5? Use the `predict()` function to answer this question.
4. Construct an ROC curve for the model from Question 2 and find the AUC as well as the threshold that maximizes sensitivity and specificity.

## **Part V**

# **Extra Topics**

# 12 Writing Reports in R Markdown

This chapter will introduce you to R Markdown, which is a document format that combines markdown text with R code. Writing in R markdown can help you write reproducible code and create polished reports to present your analyses.

## 12.1 Starting an R Markdown file

To create an R Markdown file, you will need to have RStudio installed as an application. You'll also need to install the `rmarkdown` package in addition to the `knitr` package. We also recommend the `bookdown` package, which allows us to create section, figure, and table references, as well as the `kableExtra` package for formatting your tables.

Now that you have these packages downloaded, opening a new R Markdown file is very similar to opening a new R file, which was covered in [Chapter 1](#). Just like opening a new R file, you'll want to go to File -> New File, but instead of selecting 'R Script', you'll now select 'R Markdown...'. This should bring up a window that looks like the following:

First, enter a title of your choosing for your report and type your name in the Author field - note that you can always change these later - and then click on OK. This will open an R Markdown file that has the extension .Rmd. Make sure to save this file with a suitable name in your desired location on your computer by selecting File -> Save, and then you're ready to start writing your report!

Your file should now look like this:

You will write all of the text and code that you would like to include in your report in this .Rmd file, and then you can produce a nicely formatted report from this file by 'knitting' the file. You can either knit to HTML, PDF, or WORD by clicking on the knit icon (below) from the toolbar at the top of the page and then selecting your desired output file type.

### 12.1.1 Adding Code Chunks

Each of the darker gray rectangles is called a code chunk - all of the code used to generate your report will go in these chunks, and all of your writing will go between them. Each code chunk starts with ````{r}` and ends with `````. To create a chunk, you can either

- click on this green “add chunk” symbol in the toolbar at the top of the page
- type ` ` ` {r} and ` ` `
- use the keyboard shortcut **Ctrl + Alt + I** (**Cmd + Option + I** on Macs)

To run the code in a chunk, you can either use the keyboard shortcut **Ctrl + Enter** (**Cmd + Return** on Mac), or you can use one of the following buttons at the top right of the chunks:

\* runs all chunks above the current chunk \* runs the current chunk

### 12.1.2 Customizing Chunks

You can specify whether you want to include the code and/or its various output in your final report by adding the following commands, separated by commas, to the right of the {r} at the top of the code chunk:

- `include = FALSE` makes it so that neither code nor its output will appear in your report
- `echo = FALSE` makes it so that the output of the code but not the code itself will appear in your report
- `message = FALSE`, `warning = FALSE`, and `error = FALSE` make it so that messages, warnings, and errors (respectively) that are generated from the code in the chunk won’t appear in your report

To customize a single code chunk, you can either type one of the above commands next to the {r} at the top of the code chunk by yourself or you can click on the ‘Modify Chunk Options’ symbol at the top right of the code chunk and change the settings there.

To apply the same customizations to all chunks in the document at once, you can add them to the first chunk at the very top of your R Markdown that starts with ` ` ` {r setup, include=FALSE} using the `knitr::opts_chunk$set` function. These are called the global settings. For example, using the following code for your first code chunk will make it so that none of the errors, warnings, or messages from any of the code chunks will appear in your final report. It is also good practice to load all the packages you are using for your report within this first code chunk using the `library()` function. For example, below we load the `tidyverse` and `HDSinRdata` packages.

```
 {{r setup, include = FALSE}} knitr::opts_chunk$set(echo = TRUE, warning = FALSE, error = FALSE, echo = FALSE) library(tidyverse) library(HDSinRdata)
```

If you want to display the code for your report in a code appendix, you can easily do this by creating an empty code chunk at the end of your .Rmd file with these chunk options `ref.label=knitr::all_labels()`, `echo = TRUE`, and `eval = FALSE`.

```
 {{r ref.label = knitr::all_labels(), echo = TRUE, eval = FALSE}}
```

You can also have inline R code by using single backticks around your code `r max(c(1,2,3))`. The code must start with r to be run when knit. This allows you to reference variables in

your text. For example, we could display the variance of a column in our data without having to copy the value over.

```
`r round(var(cars$speed),2)`
```

## 12.2 Formatting Text in Markdown

To add text to your report, you can simply type directly into the R Markdown file, between the code chunks. This code is formatted using markdown, which allows us to specify how to format and display the text when it is knit. For example, adding a single asterisk \* on either side of some text will italicize it, while adding a double asterisk \*\* on either side of text will make it bold. To indicate code, you can use backticks `.

```
regular text regular text  
*italicized text* italicized text  
**bolded text** bolded text  
`code text` code text
```

To create headers and sections, you can add the # symbol in front of your text. Adding more of these symbols makes the headers smaller, which is useful for making subheaders.

```
# Header  
## Smaller Header  
### Even Smaller Header
```

You can also add links [text]([www.example.com](http://www.example.com)) and images ![alt text](image.png)  
[my link](#)

# Health Data Science in R

Figure 12.1: my image

The [Markdown Guide](#) has a great [cheat sheet](#) as well as more resources for formatting markdown text.

## 12.3 Formatting Figures and Tables

Often, you'll want to include figures generated by your code in your report, and you can customize these figures by changing the chunk options for the chunks that produce them. To change the size of a figure, you can add in the chunk option `out.width="50%"` with your desired percentage of the full size. To add a nice caption to a figure in your report, you can add `fig.cap = 'Your Desired Caption..'`. To name a figure, you can add a name next to the `r` in the chunk options, without a comma, like `{r figname}`. Alternatively, you can name figures by entering text into the 'Chunk Name' field using the 'Modify Chunk Options' button at the top right of a chunk.

By default, the figures generated by your code chunks are allowed to 'float' in R Markdown - this means that the figures might move away from where they were coded or referenced in the final report. If you don't want this to happen, you can customize the chunk that contains the code to produce the figure by adding `fig.pos = "H"` to that chunk's options. If you want to prevent floating for all figures, add `fig.pos = "H"`, `out.extra = ''` to the first code chunk in the file (the one that starts with the `knitr::opts_chunk$set` function).

```
```{r myfigure, fig.cap="Figure of Average Radius vs. Diagnosis", out.width="75%",  
  fig.pos="H"}  
data(breastcancer)  
ggplot(breastcancer) +  
  geom_boxplot(aes(x = diagnosis, y = radius_mean), fill = 'lightblue') +  
  theme_bw() +  
  labs(y = "Average Radius") +  
  scale_x_discrete("Diagnosis", labels = c("Benign", "Malignant"))  
```
```

If you want to make data frames, matrices, or tables from your raw R output more polished and aesthetically pleasing, you can use the `gt` and `kableExtra` packages. Be sure to load the package you are using to the code chunk at the top of your R Markdown file that contains all of your libraries.

To demonstrate the abilities of these package, let's suppose that we wanted to display the head of the first few columns of the `breastcancer` dataset from the `HDSinRdata` package. The following code produces the following output in the knitted pdf report - you can see that it essentially just copies the raw output from R, which is rather messy.

```
```{r}  
breastcancer %>% select(id, diagnosis, radius_mean, texture_mean, perimeter_mean) %>% head  
```
```

We use the `kable()` and `kable_styling()` functions from the `kableExtra` package to produce a more nicely formatted table. The `kable()` function generates a table from a data frame. The `kable()` function allows you to specify some display options for your table. For example, you can add a caption to your table using the `caption` argument, and you can change the names of the columns in the table using the `col.names` argument. The `kable_styling()` has additional options available. Similar to the `fig.pos = H` command described for figures in the previous section, adding “`HOLD_position`” to the `kable_styling()` function will prevent the table from floating on the report; adding “`scale_down`” scales the table so that it fits in the margins of the paper. The updated code and output are below. See the documentation for the `kable` and `kable_styling` functions for more options available.

```
```{r}
breastcancer %>%
  select(id, diagnosis, radius_mean, texture_mean, perimeter_mean) %>%
  head() %>%
  kable(caption = "Head of the Breast Cancer Dataset",
        col.names = c("ID", "Diagnosis", "Mean Radius", "Mean Texture", "Mean Perimeter")) %>%
  kable_styling(latex_options = c("scale_down", "HOLD_position"))
```

```

Above, we can see that `kable` produces a much nicer table in the knitted pdf that is more suitable for a data analysis report. In [Chapter 4](#), we also introduced the `gt` package. This package is an alternative package to `kableExtra` that allows you to format each part of the table and includes options for formatting the columns, adding footers or subtitles, or grouping your table. See the [package introduction](#) for more details about this package. An example `gt` table is given below.

## 12.4 Using Bookdown for References

R Markdown automatically adds figure and table numbers to the figures and tables in your report. The `bookdown` package allows us to add references. To use this package, make sure you have installed the `bookdown` package and then add the following text to the top of your `.Rmd` file, next to “output”:

```
output:
  bookdown::pdf_document2:
    toc: false
```

The above code specifies that you would like to knit your file to a pdf document. If you would like to knit your file to an html or word document instead, you could type `bookdown::html_document2` or `bookdown::word_document2`. The `toc: false` indicates

that you do not want to include a table of contents in the report - if you do want one, you can simply type `toc:true` instead. Once you've done this, you can reference figures and tables using their names: `\@ref(fig:figname)` or `\@ref(tab:tablename)`. The knitted pdf will substitute the appropriate figure or table number into your text.

Additionally, we can reference sections by adding in labels to the section header. For example, we added the tag `#awesome` for the section below and can now reference it using `\@ref{awesome}`.

```
## Awesome Stuff {#awesome}
```

## 12.5 Adding in Equations

Another useful option in markdown is the option to add in mathematical equations. If you want to insert math equations, you can do so by writing LaTeX expressions. To write a math equation inline, you put a single dollar sign \$ on either side of your equation, and to write a math equation on its own line, you put a double dollar sign \$\$ on either side of the equation, like so:

Here's an equation that is inline with the text: `$5x^2 + 9x^3$` produces  $5x^2 + 9x^3$ . On the other hand, here's an equation that is on its own line: `$$5x^2 + 9x^3$$` produces

$$5x^2 + 9x^3$$

Here is some other LaTeX notation that you should know in order to write common equations:

\* To create a fraction, type `\frac{numerator}{denominator}`. For example, `\frac{2}{3}` produces  $\frac{2}{3}$ . \* To create a subscript, type `_`. For example, `x_{2}` produces  $x_2$ . \* To create a superscript, type `^`. For example, `x^{2}` produces  $x^2$ .

If you want to learn more about how to write in LaTeX, [Art of Problem Solving](#) provides a great reference for LaTeX symbols and [Overleaf]([https://www.overleaf.com/learn/latex/Free\\_online\\_introduction\\_to\\_LaTeX](https://www.overleaf.com/learn/latex/Free_online_introduction_to_LaTeX)) provides a helpful introduction to LaTeX in general.

## 12.6 Exercises

The exercise for this chapter is to recreate [this example pdf](#) created from an R Markdown file. You will need to use the `breastcancer` dataset from the `HDSinRdata` package.

# 13 Expanding your R Skills

Throughout this book, we have covered some popular packages as well as many of the specific functions from these packages. However, it would be impossible to cover all of the packages, functions, and options that R has. As you start to apply the tools from this book to your own work or in new settings, you may need to install and use new packages or encounter some unexpected errors. Practicing reading package documentation and responding to error messages will help you be able to expand your R skills beyond the topics covered here.

We will demonstrate these skills using the `stringr` package, which is a package that is part of the tidyverse and has several functions for dealing with text data.

```
suppressPackageStartupMessages(library(tidyverse))
suppressPackageStartupMessages(library(HDSinRdata))
```

## 13.1 Reading Documentation for New Packages

Every published package has a CRAN website. This website contains a reference manual that contains the documentation for the functions and data available in the package. Most often, the website also includes useful vignettes that give examples of how to use the functions in the package. The site also tells you what the requirements for using the package are, who the authors of the package are, and when the package was last updated. For example, take a look at the CRAN site for `stringr` and read the vignette [Introduction to String R](#).

We will use this `stringr` package to clean up text related to a PubMed search query for a systematic review. An example search query is given below and is taken from [Adatia et al. \(2021\)](#). [Out-of-hospital cardiac arrest: a systematic review of current risk scores to predict survival. American heart journal, 234, 31-41](#). Our first goal will be to extract the actual search query from the text along with all the terms used in the query. We can assume that the search query will either be fully contained in parentheses or will be a sequence of parenthetical phrases connected with AND or OR. Our goal is to extract the search query as well as all the individual search terms used in the query, but we have to get there in a series of steps.

```
sample_str <- " A systematic search will be performed in PubMed, Embase, and the
Cochrane Library, using the following search query: ('out-of-hospital cardiac
```

```
arrest' OR 'OHCA') AND ('MIRACLE 2' OR 'OHCA' OR 'CAHP' OR 'C-GRAFP' OR 'SOFA'  
OR 'APACHE' OR 'SAPS' OR 'SWAP' OR 'TTM')."
```

The first thing we want to do with the text is clean up the whitespace by removing any trailing, leading, or repeated spaces. In our example, the string starts with a trailing space and there are also multiple spaces right before the search query. Searching for “whitespace” in the stringr reference manual, we find the `str_trim()` and `str_squish()` functions. Read the documentation for these two functions. You should find that `str_squish()` is the function we are looking for and that it takes a single argument.

```
sample_str <- str_squish(sample_str)  
sample_str  
#> [1] "A systematic search will be performed in PubMed, Embase, and the Cochrane Library,"
```

## 13.2 Trying Simple Examples

The premise above is a good example of starting with a simple case. Rather than applying your function to your full data set right away, you want to first make sure that you understand how it works on a simple example on which you can anticipate what the outcome should look like. My next task will be to split the text into words and store this as a character vector. Read the documentation to determine why I used the `str_split_1()` function below. I then double check that the returned result is indeed a vector and print the result.

```
sample_str_words <- str_split_1(sample_str, " ")  
class(sample_str_words)  
#> [1] "character"  
sample_str_words  
#> [1] "A" "systematic" "search"  
#> [4] "will" "be" "performed"  
#> [7] "in" "PubMed," "Embase,"  
#> [10] "and" "the" "Cochrane"  
#> [13] "Library," "using" "the"  
#> [16] "following" "search" "query:"  
#> [19] "('out-of-hospital'" "cardiac" "arrest'"  
#> [22] "OR" "'OHCA'") "AND"  
#> [25] "('MIRACLE'" "2'" "OR"  
#> [28] "'OHCA'" "OR" "'CAHP'"  
#> [31] "OR" "'C-GRAFP'" "OR"  
#> [34] "'SOFA'" "OR" "'APACHE'"
```

```
#> [37] "OR"           "'SAPS'"          "OR"
#> [40] "'SWAP'"      "OR"             "'TTM')."
```

We now want to identify words in this vector that have starting and/or end parentheses. The function `grep1()` takes in a character vector `x` and a pattern to search for. It returns a logical vector for whether or not each element of `x` has a match for that pattern.

```
grep1(sample_str_words, ")")
#> Warning in grep1(sample_str_words, ")"): argument 'pattern' has length
#> > 1 and only the first element will be used
#> [1] FALSE
```

Huh, that didn't match what I expected! I expected to have multiple TRUE/FALSE values outputted - one for each word. Let's read the documentation again.

### 13.3 Deciphering Error Messages and Warnings

The warning message above will give us a good clue for what went wrong. It says that the inputted pattern has length  $> 1$ . However, the pattern I gave it is a single character. In fact, I specified the arguments in the wrong order. Let's try again. This time I specify `x` and `pattern`.

```
grep1(x=sample_str_words, pattern=")")
#> [1] FALSE FALSE
#> [12] FALSE FALSE
#> [23] TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
#> [34] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE TRUE
```

That worked! However, it won't work if we change that to a starting parentheses. Try it out for yourself to see this. The error message says that it is looking for an end parentheses. In this case, the documentation does not help us. Let's try googling “stringr find start parentheses”. The first search result for me is a [stack overflow question](#) that helps us out. We read that we need to use backslashes to tell R to read the parentheses literally rather than as a special character used in a regular expression.

```
grep1(x=sample_str_words, pattern="\\"(")
#> [1] FALSE FALSE
#> [12] FALSE FALSE FALSE FALSE FALSE FALSE FALSE TRUE FALSE FALSE FALSE
#> [23] FALSE FALSE TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
#> [34] FALSE FALSE
```

When a function doesn't return what we expect it to, it is a good idea to first test whether the arguments we gave it match what we expect, then to re-read the documentation, and then to look for other resources for help. For example, we could check that `sample_str_words` is indeed a character vector, then re-read the `stringr` documentation, and then google our problem.

### 13.3.1 Debugging Code

The code below is supposed to extract the search query from the text as well as find the individual search terms used in the query. However, the code is incorrect. You can try out to two test strings given to see why the code output is wrong. Practice reading through the code to understand what it is trying to do. The comments are there to help explain the steps, but you may also want to print the output to figure out what it is doing.

```
sample_strA <- " A systematic search will be performed in PubMed, Embase, and the  
Cochrane Library, using the following search query: ('out-of-hospital cardiac  
arrest' OR 'OHCA') AND ('MIRACLE 2' OR 'OHCA' OR 'CAHP' OR 'C-GRAFP' OR 'SOFA'  
OR 'APACHE' OR 'SAPS' OR 'SWAP' OR 'TTM')."  
  
sample_strB <- "Searches will be conducted in MEDLINE via PubMed, Web of Science,  
Scopus and Embase. The following search strategy will be  
used:(child OR infant OR preschool child OR preschool children OR preschooler  
OR pre-school child OR pre-school children OR pre school child OR pre school  
children OR pre-schooler OR pre schooler OR children OR adolescent OR adolescents)AND  
(attention deficit disorder with hyperactivity OR ADHD OR attention deficit  
disorder OR ADD OR hyperkinetic disorder OR minimal brain disorder) Submitted "  
  
sample_str <- sample_strB  
  
# separate parentheses, remove extra whitespace, and split into words  
sample_str <- str_replace(sample_str, "\\)", " \\) ")  
sample_str <- str_replace(sample_str, "\\(", " \\( ")  
sample_str <- str_squish(sample_str)  
sample_str_words <- str_split_1(sample_str, " ")  
  
# find indices with parentheses  
end_ps <- grepl(x=sample_str_words, pattern="\\)")  
start_ps <- grepl(x=sample_str_words, pattern="\\(")  
  
# find words between first and last parentheses  
search_query <- sample_str_words[ which(end_ps)[1]:which(start_ps)[1]]
```

```

search_query <- paste(search_query, collapse=" ")
search_query
#> [1] ") adolescents OR adolescent OR children OR schooler pre OR pre-schooler OR childre

# find search terms
search_terms <- str_replace_all(search_query, "\\)", "")
search_terms <- str_replace_all(search_query, "\\(", "")
sample_terms <- str_squish(search_query)
search_terms <- str_split_1(search_terms, " AND | OR ")
search_terms
#> [1] "adolescents"      "adolescent"          "children"
#> [4] "schooler pre"     "pre-schooler"        "children school pre"
#> [7] "child school pre" "children pre-school" "child pre-school"
#> [10] "preschooler"     "children preschool" "child preschool"
#> [13] "infant"          "child"

```

## 13.4 Video Solution

We will show how we can test and fix the code above by using some simple debugging principles.

<https://www.youtube.com/embed/2yfjXyAbbK8>

## 13.5 General Programming Tips

As you write more complex code and functions, it is inevitable that you will run into errors or unexpected behavior. Below are some simple principles that are applicable to debugging in any setting. When it comes to testing code, a good mantra is *test early and test often*. So, try to avoid writing too much code before running and checking that the results match what you expect.

1. Check that all parentheses (), brackets [], and curly braces {} match.
2. Check that object names are correct.
3. Check whether you use the same name for different objects or whether you use different names for the same object. You can do this by using the `ls()` function to find all current objects.
4. Check that the input arguments to a function match what is expected.

5. Try simple examples first. You can use the documentation or vignette examples for ideas.
6. Localize your error by checking the values of objects at different points.
  
7. Modify your code one piece at a time before checking it to avoid introducing new errors.
  
8. Google error messages you don't understand. R's messages can sometimes hint at what the error might stem from, but they are not always direct.

## 13.6 Exercises

1. Suppose we want to replace the words "Thank you" in the following string with the word "Thanks". Why does the below code fail? How can we correct it?

```
string <- "Congratulations on finishing the book! Thank you for reading it."
str_sub(string, c(35, 42)) <- "Thanks"
string
#> [1] "Congratulations on finishing the bThanks"
#> [2] "Congratulations on finishing the book! ThThanks"
```

2. The code below uses the `NHANESsample` data from the `HDSinRdata` package. The goal of the code is to plot the worst diastolic blood pressure reading against the worst systolic blood pressure reading for each patient, colored by hypertension status. However, the code currently generates an error message. What is wrong with the code below? There are four errors for you to identify and fix.

```
data(NHANESsample)

nhanes_df <- NHANESsample %>% mutate(worst_DBP = max(DBP1, DBP2, DBP3, DBP4),
                                         worst_SBP = max(SBP1, SBP2, SBP3, SBP4))

ggplot() %>% geom_point(data = nhanes_df, aes(x = worst_SBP, y = worst_DBP), color = HYP)
```

3. The code below uses the `breastcancer` data from the `HDSinRdata` package. The goal is to create a logistic regression model for whether or not the diagnosis is benign or malignant and then to create a calibration plot for the model, following the code from [Chapter 11](#). What is wrong with the code below? Debug it. Hint: there are three separate errors.

```

data(breastcancer)

model <- glm(diagnosis ~ smoothness_worst + symmetry_mean + texture_se + radius_mean,
             data = breastcancer, family = binomial)

pred_probs <- predict(model)

num_cuts <- 10
calib_data <- data.frame(prob = pred_probs,
                           bin = cut(pred_probs, breaks = num_cuts),
                           class = mod_start$y)

calib_data <- calib_data %>%
  group_by(bin) %>%
  summarize(observed = sum(class)/n(),
            expected = sum(prob)/n(),
            se = sqrt(observed*(1-observed)/n()))

calib_data

ggplot(calib_data) +
  geom_abline(intercept = 0, slope = 1, color="red") +
  geom_errorbar(aes(x = expected, ymin=observed-1.96*se,
                     ymax=observed+1.96*se),
                 colour="black", width=.01) +
  geom_point(aes(x = expected, y = observed)) +
  labs(x="Expected Proportion", y="Observed Proportion") +
  theme_minimal()

```