Programming and Quantitative Skills: R

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What is R and RStudio?

- R is a *programming language* which specializes in statistical computing and graphics.
  - A programming language is a way to instruct a computer to perform operations via written text.
  - When programming, we need to be very exact. Otherwise the computer will throw and error or do something we didn't intend it to do!
- RStudio is a desktop application where you can write R code, execute R programs, and view plots created by R.

Why Learn R?

R has many benefits over some alternatives:

- R is free and open source.
- Large active community creating packages and providing support.
- Easier to learn than some alternatives.
- Availability of RStudio for free.
- R is extremely versatile. For example, these slides were made in RStudio!

Learning R also doesn't end after the exam for this course. In the 2nd year you will take Statistics 2 where you will learn how to estimate and use various statistical models in R.

Installing R

- To download and install R, go to https://mirror.lyrahosting.com/CRAN.
- To download and install RStudio, go to https://posit.co/download/rstudio-desktop/.

The R Console

- We can perform calculations in the Console tab in RStudio.
- At the most basic level, we can use it as a simple calculator:
  - Add: `2 + 3`
  - Subtract: `5 - 3`
  - Multiply: `2 * 3`
  - Divide: `3 / 2`
  - Exponentiation: `2^3`
  - Combining operations: `(2 + 4) / (4 * 2)`

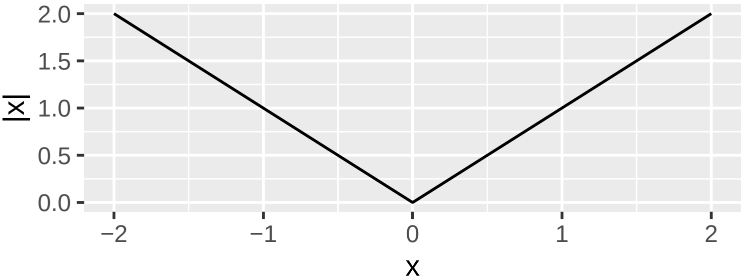
R Functions

- Just like Excel, R has functions.
- These functions work in a very similar way:
  - Functions have names, and we provide *arguments* to functions inside parentheses.
- In the next few slides we will see some examples of mathematical functions and how to evaluate them in R.

Absolute Value

- The absolute value function turns negative numbers into positive ones and has no effect on zero or positive numbers.

$$|x| = \begin{cases} x & \text{if } x \geq 0 \\ -x & \text{otherwise} \end{cases}$$



Absolute Value in R

- The absolute value function in R is called `abs`. We can use it as follows:

```r
abs(-2)
```

```
[1] 2
```

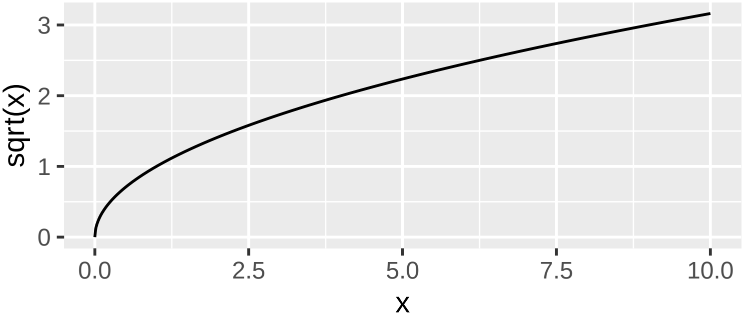
```r
abs(3)
```

```
[1] 3
```

- We can see help about a function using `help(abs)` or `?abs`

Principal Square Roots

- The square root of a number is the y that solves $y^2 = x$.
- If $x = 4$, both $y = -2$ and $y = 2$ solve $y^2 = x$.
- The principal square root is the positive y solving this.



Principal Square Roots in R

- We can use the `sqrt()` function or take to the power of $\frac{1}{2}$ to take the square root.

```
sqrt(9)
```

```
[1] 3
```

```
9^(1/2)
```

```
[1] 3
```

- The cubed root is the y that solves $y = x^3$. We can calculate this in R by taking the power of $\frac{1}{3}$.

```
8^(1/3)
```

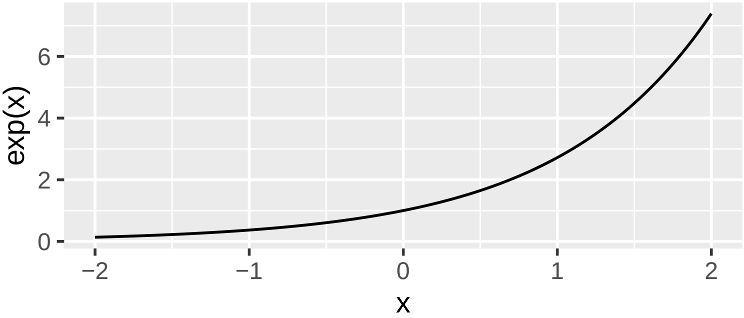
```
[1] 2
```

The Exponential Function

The exponential function is a very common function in statistics:

$$e^x = \lim_{n \to \infty} \left(1 + \frac{x}{n}\right)^n$$

Note: you don't need to know this function for the exam.



The Exponential Function in R

- In R we use the `exp( )` function to calculate the exponential of a number:

```r
exp(0)
```

```
[1] 1
```

```r
exp(1)
```

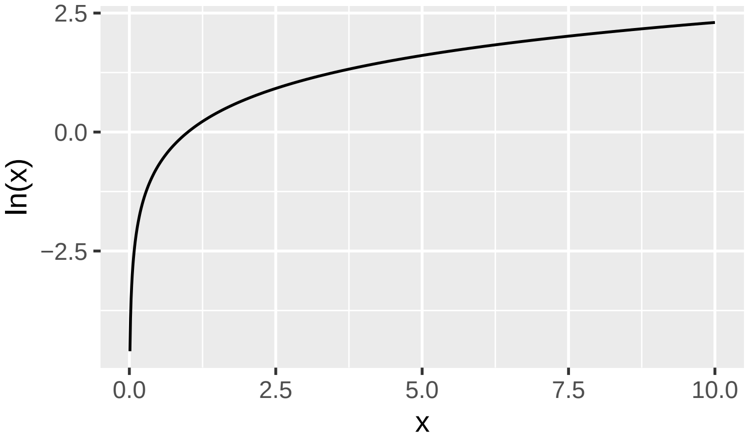
```
[1] 2.718282
```

The Logarithm

- Another common mathematical function is the logarithm, which is like the reverse of exponentiation.
- The log of a number x to a base b, denoted $\log_b(x)$, is the number of times we need to multiply b by itself to get x.
- For example, $\log_{10}(100) = 2$, because $10 \times 10 = 100$. We need to multiply the base $b = 10$ by itself twice to get to $x = 100$.

The Natural Logarithm

- A special logarithm is the natural logarithm, $\log_e(x)$, which is the logarithm to the base $\exp(1) = e^1 \approx 2.7183$. This is also written as $\ln(x)$.



The Logarithm in R

- In R we use the `log()` function to calculate the natural logarithm:

```
log(1)
```

```
[1] 0
```

- We can calculate the logarithm of a number to a different base using the `base` argument. For example, for $\log_{10}(100)$:

```
log(100, base = 10)
```

```
[1] 2
```

The Assignment Operator: `<-`

- We can store objects using the *assignment operator*, `<-`.
- For example:

```
a <- 2
b <- 3
```

- a and b are then visible in the **Environment** tab in RStudio.
- We can then use a and b for calculations:

```
a + b
```

```
[1] 5
```

Common Object Types: Numerical, Logical and Character

- Numerical vectors (list of numbers):

```r
a <- c(1, 3, 7, 2)
```

- Logical vectors (list of Yes/No responses):

```r
a <- c(TRUE, FALSE, TRUE, TRUE)
```

- Character vectors (list of letters/words):

```r
a <- c("programming", "and", "quantitative", "skills")
```

Common Object Types: Factors

- Categorical variables are stored in R as “factors”.
- For example, imagine a survey asking how long it took for people to get to campus (in minutes) and their travel mode (one of “cycle”, “train”, or “walk”).
- You could store these variables as a numerical and a character variable:

```
time <- c(25, 20, 15, 10, 17, 30)
travel_mode <- c("train", "train", "walk",
                 "cycle", "walk", "train")
```

- But if we tell R that this travel mode variable is a categorical variable, it will be useful for operations that we will learn later. We can convert this to a factor using the `factor` function:

```
travel_mode <- factor(travel_mode)
```

Common Object Types: Data Frames and Lists

- A `data.frame` collects vectors of the same length into a single dataset.
- We can convert the `time` and `travel_mode` variables into a `data.frame` as follows:

```
df <- data.frame(travel_mode, time)
```

- We can also "View" it in RStudio by clicking on it in the Environment tab.
- A `data.frame` is actually a special type of list:

```
my_list <- list(x = 1:3, y = TRUE, z = c("a", "b"))
```

- While vectors must have all elements of the same type (numeric/logical/character/factor), lists can have elements of any type *and any length*.
- Dataframes can have columns of different types, but all columns must have the same length.

Indexing Vectors with Numbers

- The elements of a vector like:

```r
a <- c(1, 2, 4, 3, 2)
```

  are indexed 1-5.

- We can extract elements from this vector using these indices:

```r
a[3]
```

```
[1] 4
```

```r
a[c(1, 3, 4)]
```

```
[1] 1 4 3
```

Indexing Vectors with Logical Vectors

- We can also index vectors using an equal-length logical vector, where we exract only the elements that are TRUE:

```r
a <- c(1, 2, 4, 3, 2)
a[c(TRUE, FALSE, TRUE, TRUE, FALSE)]
```

```
[1] 1 4 3
```

Sequences

We can create vectors that are sequences of numbers in different ways:

```
1:10
```

```
 [1]  1  2  3  4  5  6  7  8  9 10
```

```
10:1
```

```
 [1] 10  9  8  7  6  5  4  3  2  1
```

```
seq(from = 10, to = 100, by = 10)
```

```
 [1]  10  20  30  40  50  60  70  80  90 100
```

```
seq(from = 0, to = 1, length.out = 5)
```

```
[1] 0.00 0.25 0.50 0.75 1.00
```

Repeating Numbers and Vectors

To save time typing, we can repeat numbers and vectors with the `rep()` function:

```
rep(1, times = 20)
```

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

```
rep(1:3, times = 4)
```

```
 [1] 1 2 3 1 2 3 1 2 3 1 2 3
```

```
rep(1:3, each = 4)
```

```
 [1] 1 1 1 1 2 2 2 2 3 3 3 3
```

Summary Statistics for Vectors

```
a <- 1:10
a
```

```
 [1]  1  2  3  4  5  6  7  8  9 10
```

```
length(a)
```

```
[1] 10
```

```
min(a)
```

```
[1] 1
```

```
max(a)
```

```
[1] 10
```

Summary Statistics for Vectors

```r
mean(a)
```

```
[1] 5.5
```

```r
median(a)
```

```
[1] 5.5
```

```r
sum(a)
```

```
[1] 55
```

```r
summary(a)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
   1.00    3.25    5.50    5.50    7.75   10.00
```

Tabulate a Vector

```r
a <- c(1, 3, 2, 4, 4, 2, 4)
table(a)
```

```
a
1 2 3 4
1 2 1 3
```

Comparing Numerical Vectors

```
a <- 1:5
b <- 5:1
a
```

```
[1] 1 2 3 4 5
```

```
b
```

```
[1] 5 4 3 2 1
```

```
a < b
```

```
[1]  TRUE  TRUE FALSE FALSE FALSE
```

```
a <= b
```

```
[1]  TRUE  TRUE  TRUE FALSE FALSE
```

Comparing Numerical Vectors

```
a == b
```

```
[1] FALSE FALSE  TRUE FALSE FALSE
```

```
a != b
```

```
[1]  TRUE  TRUE FALSE  TRUE  TRUE
```

```
a >= b
```

```
[1] FALSE FALSE  TRUE  TRUE  TRUE
```

```
a > b
```

```
[1] FALSE FALSE FALSE  TRUE  TRUE
```

Comparing Logical Vectors

```
a <- c(TRUE, TRUE, FALSE, FALSE)
b <- c(TRUE, FALSE, TRUE, FALSE)
```

We use & for *logical AND*, | for *logical OR* and `!` for *logical NOT*.

```
a & b
```

```
[1]  TRUE FALSE FALSE FALSE
```

```
a | b
```

```
[1]  TRUE  TRUE  TRUE FALSE
```

```
!a
```

```
[1] FALSE FALSE  TRUE  TRUE
```

R Scripts

- When working on a project, it's often better to write all the commands you want to run in an *R script* instead of directly into the console:
  - It documents and saves your work.
  - It makes your work shareable and reproduceable.
  - You can edit earlier commands in a chain of commands.
  - It's easier to spot mistakes.
- There are different ways of "running" an R script:
  - Selecting all or a subset of lines and hitting "Run".
  - Sourcing "with echo" and "without echo".

Commenting in R Scripts

- When writing code it's good practice to write "comments" to help others (and you!) understand your code.
- Anything written after a # symbol is ignored by the R console. So we precede all comments with a #.

```
# Set values of a and b:
a <- 2
b <- 3
print(a + b)  # Compute the sum of a and b and print:
```

```
[1] 5
```

- Commenting is also useful if you want to temporarily disable a certain part of your script. You just need to put a # before the commands you want to disable.
  - This is called "commenting out".
  - Select the lines you want to comment out, then go to Code $\longrightarrow$ `Comment/Uncomment Lines`.

CSV files

- The most common way we read data into R is through CSV (comma-separated values) files.
- These are plain text files with a `.csv` extension.
- We would store our travel mode survey data in a CSV file like this:

```
travel_mode,time
train,25
train,20
walk,15
cycle,10
walk,17
train,30
```

CSV files: Commas in data points

- Each line needs to have the same number of commas.
- If data points contain commas themselves (e.g. suppose a category was `train, cycle`), we need to wrap the data points with quotes.
- So often you will see CSV files where the text is wrapped in quotes:

```
"travel_mode","time"
"train",25
"train",20
"walk",15
"cycle",10
"walk",17
"train",30
```

CSV files: Comma decimal separators

- In continental Europe, commas are used as decimal separators: "one and a half" is written as 1,5.
- Clearly this will cause problems with CSV files!
- So sometimes you might see files with `;` delimiting variables instead of `,`.
- An example of that would be:

```
"travel_mode";"time"
"train";25,0
"train";20,0
"walk";15,0
"cycle";10,0
"walk";17,0
"train";30,0
```

- When this happens, we need to tell R that the file is using a `;` separator.
- In the exam, however, we'll deal exclusively with more standard CSV files.

Reading CSV files into R

- In order to read a CSV file into R, we need to tell R where the file is located on our computer.
- There are three different approaches to do this:
  1. The absolute path method
  2. The relative path method
  3. The RStudio Projects method (my recommendation!)
- For this we save the travel mode data in a file called `test.csv`.

Reading CSV files into R: The Absolute Path Method

- This approach involves giving R the full path to the file.
- On Windows, the full path of would look something like `C:\Users\username\Documents\test.csv`.
- However, the backslash has a special purpose in R so we can't use this.
- We need to use either forward slashes ("/") or *double-backslashes* ("\"):
  - `C:/Users/username/Documents/test.csv`
  - `C:\\Users\\username\\Documents\\test.csv`
- The fastest way to get the full path to a file is with the `file.choose()` command.
- Run the command, navigate to the file, and then the full file path with appear in the console. You can then copy this to your clipboard.
- You can then paste this as an argument into the `read.csv()` command:

```r
df <- read.csv("C:\\Users\\username\\Documents\\test.csv")
```

- When we use this approach, it doesn't matter what the current working directory of the R process is.

Reading CSV files into R: The Relative Path Method

- We can find out what the current working directory is with `getwd()`.
- To change it to the `Documents` folder, we can use the `setwd()` command.
- When the R process is in the working directory with the data, we only need to provide the name of the file in the `read.csv()` command.
- The steps would then be:

```
setwd("C:\\Users\\username\\Documents\\")
df <- read.csv("test.csv")
```

- Suppose the full path of the file was actually `"C:\\Users\\username\\Documents\\data\\test.csv"`
- We could then read in the data from the `Documents` folder by only giving the *relative path* to the file, which is `"data\\test.csv"`:

```
setwd("C:\\Users\\username\\Documents\\")
df <- read.csv("data\\test.csv")
```

Reading CSV files into R: The RStudio Projects Method

- If you share your code with someone, they will have to edit these lines that read in the data, or change the working directory. This is not ideal!
- A better way to deal with file paths is by using the RStudio Project feature.
- Suppose you saved your data in a folder called PQS on your computer.
- To go `File` $\longrightarrow$ `New Project`, choose “Existing Directory”, and navigate to the PQS folder.
- When you are in the PQS project, RStudio automatically changes the current working directory to that folder. Then you don’t need to provide the full file path, or use the `setwd()` command.
- Therefore I recommend this approach over the previous methods.

R Packages: Installing a Package

- Up to now, all the functions we have been using come by default with R.
  - We call the default functionality "base R".
- But people have written *packages* that expand the functionality of R to do more things.
- For example, base R is not able to read in data from an Excel file.
  - But there are several packages that can do this.
  - We'll learn how to do this using the `readxl` package.
- To install a package, you can use the command:

```
install.packages("readxl")
```

- Alternatively, you can install the package using `Tools` $\longrightarrow$ `Install Packages...` in RStudio.

R Packages: Loading and Using a Package

- R doesn't load up the functions of all the installed packages by default. We also need to *load* a package after we install it.
- We can do this with the `library()` command:

```
library(readxl)
```

- If a package is not installed, the library function will return an error.
- To read in a file called `test.xlsx` in the current working directory, we do:

```
df <- read_excel("test.xlsx")
```

- The `read_excel()` function loads the data as a `tibble`, which is like a `data.frame` but with a few extra features. We can force the data to be a plain `data.frame` with:

```
df <- data.frame(read_excel("test.xlsx"))
```

Dataframes: Eredivisie Data

```
                team wins draws losses goals_for goals_against
1                 AZ   20     7      7        68            35
2               Ajax   20     9      5        86            38
3          Excelsior    9     5     20        32            71
4           FC Emmen    6    10     18        33            65
5       FC Groningen    4     6     24        31            75
6          FC Twente   18    10      6        66            27
7         FC Utrecht   15     9     10        55            50
8        FC Volendam   10     6     18        42            71
9          Feyenoord   25     7      2        81            30
10   Fortuna Sittard   10     6     18        39            62
11   Go Ahead Eagles   10    10     14        46            56
12               NEC    8    15     11        42            45
13               PSV   23     6      5        89            40
14      RKC Waalwijk   11     8     15        50            64
15        SC Cambuur    5     4     25        26            69
16  Sparta Rotterdam   17     8      9        60            37
17           Vitesse   10    10     14        45            50
18    sc Heerenveen    12    10     12        44            50
```

Dataframes: Indexing

- We can get the 2nd row and 3rd column of `df` with `df[2, 3]`.
- We can the team name and number of wins variables for Ajax, Feyenoord and PSV with `df[c(2, 9, 13), c(1, 2)]`.
- We can extract all variables for Ajax with `df[2, ]`.
- We can extract all values for “goals for” with `df[, 5]`.
- We can also extract all values for a column with a variable name:
  - `df$goals_for`.
  - `df[, "goals_for"]`.
  - `df[["goals_for"]]`.
- We can extract several columns with:
  - `df[, c("team", "goals_for")]`
- To get the rows for all teams with at least 20 wins: `df[df$wins >= 20, ]`.

Dataframes: Creating Variables - Goal Difference

```r
df$goal_diff <- df$goals_for - df$goals_against
head(df)
```

```
          team wins draws losses goals_for goals_against goal_diff
1           AZ   20     7      7        68            35        33
2         Ajax   20     9      5        86            38        48
3    Excelsior    9     5     20        32            71       -39
4     FC Emmen    6    10     18        33            65       -32
5 FC Groningen    4     6     24        31            75       -44
6    FC Twente   18    10      6        66            27        39
```

Dataframes: Creating Variables - Total Points

$$\text{Points} = 3 \times \text{Wins} + 1 \times \text{Draws} + 0 \times \text{Losses}$$

```
df$total_points <- 3 * df$wins + df$draws
head(df[, c("team", "wins", "draws", "losses", "total_points")])
```

```
          team wins draws losses total_points
1           AZ   20     7      7           67
2         Ajax   20     9      5           69
3    Excelsior    9     5     20           32
4     FC Emmen    6    10     18           28
5 FC Groningen    4     6     24           18
6    FC Twente   18    10      6           64
```

Dataframes: Creating Variables - Team Ranking

```
df <- df[order(df$total_points, df$goal_diff, decreasing = TRUE), ]
df$ranking <- 1:nrow(df)
head(df[, c("team", "total_points", "goal_diff", "ranking")])
```

```
                team total_points goal_diff ranking
9          Feyenoord           82        51       1
13               PSV           75        49       2
2               Ajax           69        48       3
1                 AZ           67        33       4
6          FC Twente           64        39       5
16  Sparta Rotterdam           59        23       6
```

Dataframes: Creating Variables - Relegation Status

```r
df$relegation_status <- ""
df$relegation_status[df$ranking < 16] <- "No relegation"
df$relegation_status[df$ranking == 16] <- "Relegation playoffs"
df$relegation_status[df$ranking %in% 17:18] <- "Automatic relegation
```

```r
df[, c("team", "ranking", "relegation_status")]
```

```
                team ranking    relegation_status
9          Feyenoord       1        No relegation
13               PSV       2        No relegation
2               Ajax       3        No relegation
1                 AZ       4        No relegation
6          FC Twente       5        No relegation
16  Sparta Rotterdam       6        No relegation
7          FC Utrecht      7        No relegation
18     sc Heerenveen       8        No relegation
14      RKC Waalwijk       9        No relegation
17           Vitesse      10        No relegation
11   Go Ahead Eagles      11        No relegation
12               NEC      12        No relegation
10   Fortuna Sittard      13        No relegation
8        FC Volendam      14        No relegation
3          Excelsior      15        No relegation
4           FC Emmen      16  Relegation playoffs
15        SC Cambuur      17 Automatic relegation
5       FC Groningen      18 Automatic relegation
```

The %in% Operator

- When we write a `%in%` b we are checking for each element in a if there is a *matching* element *somewhere* in b.

```
a <- 1:6
b <- c(3, 5, 7)
a %in% b
```

```
[1] FALSE FALSE  TRUE FALSE  TRUE FALSE
```

An equivalent but longer way of doing the same thing would be:

```
a == b[1] | a == b[2] | a == b[3]
```

```
[1] FALSE FALSE  TRUE FALSE  TRUE FALSE
```

Dataframes: Summarizing a Dataframe

The `summary()` command gives the summary statistics of all variables in `df`:

```
summary(df[, c("team", "wins", "draws", "losses")])
```

```
     team                wins           draws            losses     
 Length:18          Min.   : 4.00   Min.   : 4.000   Min.   : 2.00  
 Class :character   1st Qu.: 9.25   1st Qu.: 6.000   1st Qu.: 7.50  
 Mode  :character   Median :10.50   Median : 8.000   Median :13.00  
                    Mean   :12.94   Mean   : 8.111   Mean   :12.94  
                    3rd Qu.:17.75   3rd Qu.:10.000   3rd Qu.:18.00  
                    Max.   :25.00   Max.   :15.000   Max.   :25.00  
```

Dataframes: Peaking at your data

- We use `head(df, n = 4)` to see the first 4 rows of `df`. `head(df)` on its own shows 6 rows by default.
- We use `tail(df, n = 2)` to see the last 2 rows of `df`.

```
nrow(df)  # see the number of rows in df
```

```
[1] 18
```

```
ncol(df)  # see the number of columns in df
```

```
[1] 10
```

```
dim(df)   # see both the number of rows and number of columns in df
```

```
[1] 18 10
```

Dataframes: See all variable names

- `names(df)` shows the variable names of all variables in `df`.

```
names(df)
```

```
 [1] "team"               "wins"               "draws"
 [4] "losses"             "goals_for"          "goals_against"
 [7] "goal_diff"          "total_points"       "ranking"
[10] "relegation_status"
```

- Later we will learn how to use this command to change the names of variables in `df`.

Data Cleaning

Very often when we have a spreadsheet, we need to do some “cleaning” before we can work with it in R.

This can happen when:

- The data don’t start at the top of the file because the first few rows contain some other information.
- The dates are not formatted correctly.
- Numbers are interpreted as characters.
- The data contain extra columns that we don’t want.
- There are rows with missing data that we want to omit.
- The variable names are not what we want them to be.

ASML Stock Price Data

We will learn how to clean data with the `asml-trades.csv` data.

The variable names are:

- `Date`: The date the data from that row are from.
- `Open`: The opening price of the stock on that day.
- `High`: The highest price the stock traded at on that day.
- `Low`: The lowest price the stock traded at on that day.
- `Last`: The price of the last-traded stock at on that day.
- `Close`: The closing price of the stock on that day.
- `Number.of.Shares`: The number of shares traded that day.
- `Number.of.Trades`: The number of trades made that day.

Skipping Rows

If the data don't begin at the top of a file, you can tell R to ignore the empty rows with the `skip` option:

```
df <- read.csv("asml-trades.csv", skip = 3)
```

```
summary(df)
```

```
     Date                Open            High            Low       
 Length:521         Min.   :394.7   Min.   :408.2   Min.   :375.8  
 Class :character   1st Qu.:535.5   1st Qu.:545.5   1st Qu.:525.8  
 Mode  :character   Median :592.1   Median :597.4   Median :582.5  
                    Mean   :589.2   Mean   :597.5   Mean   :579.6  
                    3rd Qu.:645.5   3rd Qu.:652.5   3rd Qu.:636.1  
                    Max.   :770.5   Max.   :777.5   Max.   :764.2  
                    NA's   :6       NA's   :6       NA's   :6      
      Last           Close       Number.of.Shares   Number.of.Trades  
 Min.   :397.4   Min.   :397.4   Length:521         Length:521        
 1st Qu.:535.9   1st Qu.:535.9   Class :character   Class :character  
 Median :589.4   Median :589.4   Mode  :character   Mode  :character  
 Mean   :588.4   Mean   :588.4                                        
 3rd Qu.:644.0   3rd Qu.:644.0                                        
 Max.   :770.5   Max.   :770.5                                        
 NA's   :6       NA's   :6                                            
 Print.table    
 Mode:logical   
 NA's:521       
```

Formatting Dates

The date variable was read in as a character instead of a date.

```
head(df$Date, n = 3)
```

```
[1] "31/8/2021" "1/9/2021"  "2/9/2021"
```

The dates are in the format "dd/mm/yyyy". We can convert these to dates using the `as.Date()` function, telling R the format the dates are in:

```
df$Date <- as.Date(df$Date, format = "%d/%m/%Y")
```

```
summary(df$Date)
```

```
        Min.      1st Qu.       Median         Mean      3rd Qu.         Max.
"2021-08-31" "2022-03-01" "2022-08-30" "2022-08-29" "2023-02-28" "2023-08-29"
```

Formatting Dates: More Examples

```
as.Date("12/31/2023", format = "%m/%d/%Y")
```

```
[1] "2023-12-31"
```

```
as.Date("31-12-2023", format = "%d-%m-%Y")
```

```
[1] "2023-12-31"
```

```
as.Date("31/12/23", format = "%d/%m/%y")
```

```
[1] "2023-12-31"
```

```
as.Date("31 Dec 2023", format = "%d %b %Y")
```

```
[1] "2023-12-31"
```

```
as.Date("31 December 2023", format = "%d %B %Y")
```

```
[1] "2023-12-31"
```

Converting Characters to Numbers

- Although most values are numbers, there are some elements with `"None"` in the variables `Number.of.Shares` and `Number.of.Trades`.
- These character elements force the entire variable to be character, because all elements in a vector must have the same type.
- If we convert the character elements to NA (missing values), we can convert the variable to a numeric vector:

```
df$Number.of.Shares[df$Number.of.Shares == "None"] <- NA
df$Number.of.Shares <- as.numeric(df$Number.of.Shares)
```

- We could skip the step of converting character elements to NA, but then R would warn us: `NAs introduced by coercion`.

Deleting Variables

We can delete variables by assigning `NULL` to that variable.

```
df$Print.table <- NULL
```

Alternatively we can drop variables using the column index of the variables we want to drop. We can drop the 9th variable (`Print.table`) with:

```
df <- df[, -9]
```

Dropping Rows with Missing Data

- For all variables apart from the date we having missing data on 6 rows. Let's take a look at which dates these are:

```
df$Date[is.na(df$Open)]
```

```
[1] "2022-04-15" "2022-04-18" "2022-12-26" "2023-04-07" "2023-04-10"
[6] "2023-05-01"
```

- These are dates around Easter and Christmas when the stock market is closed.
- We can drop rows with any missing variables with the `na.omit()` function.

```
nrow(df)
```

```
[1] 521
```

```
df <- na.omit(df)
nrow(df)
```

Renaming Variables

We can change a variable name using its column index as follows:

```
names(df)[7] <- "num_shares"
```

We can change a variable name using its current name as follows:

```
names(df)[names(df) == "Number.of.Trades"] <- "num_trades"
```

We can change multiple variable names at once with:

```
names(df)[2:5] <- c("open", "high", "low", "last")
```

Renaming Variables: Converting to Lower Case

We can convert characters to lower case with the `tolower()` function:

```
test <- c("hello!", "HELLO!", "Hello!", "HeLlO!")
tolower(test)
```

```
[1] "hello!" "hello!" "hello!" "hello!"
```

We can convert all variable names to lower case with:

```
names(df) <- tolower(names(df))
names(df)
```

```
[1] "date"       "open"       "high"       "low"        "last"
[6] "close"      "num_shares" "num_trades"
```

Introduction to Plotting

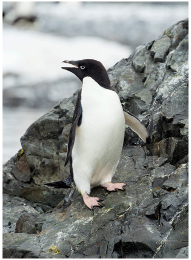
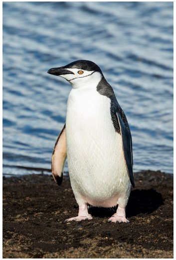
- We will now learn how to plot data with R.
- We will learn how to make:
  - Histograms: these display the distribution of a numeric variable.
  - Bar charts: these display frequencies of values for numeric or categorical data.
  - Scatter plots: these display the relationship between two numeric variables.
- There are two ways to make these plots:
  1. The “base R” approach (using built-in plotting functions in R)

     These are quick and easy to make, but don’t look very nice.
  2. The “ggplot” approach (using the `ggplot2` package).

     These require more code, but are prettier and more customizable.

The Palmer Penguins Dataset

- We will use this famous dataset to demonstrate plotting.
- It contains the weight, gender, flipper length, and bill length and depth for 3 types of penguins: the adelie, the chinstrap and gentoo.


We can load the dataset with:

```r
install.packages("palmerpenguins")
library(palmerpenguins)
data(penguins)
```

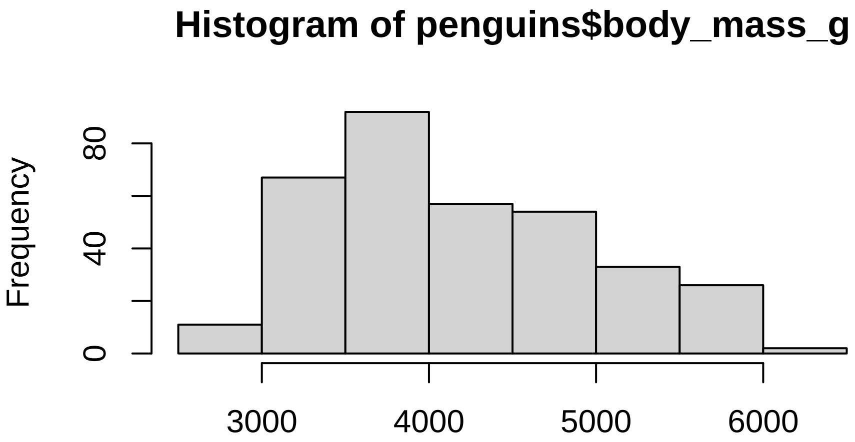
Summarizing the Data

```r
summary(penguins)
```

```
      species          island    bill_length_mm  bill_depth_mm  
 Adelie   :152   Biscoe   :168   Min.   :32.10   Min.   :13.10  
 Chinstrap: 68   Dream    :124   1st Qu.:39.23   1st Qu.:15.60  
 Gentoo   :124   Torgersen: 52   Median :44.45   Median :17.30  
                                 Mean   :43.92   Mean   :17.15  
                                 3rd Qu.:48.50   3rd Qu.:18.70  
                                 Max.   :59.60   Max.   :21.50  
                                 NA's   :2       NA's   :2      
 flipper_length_mm  body_mass_g       sex           year     
 Min.   :172.0     Min.   :2700   female:165   Min.   :2007  
 1st Qu.:190.0     1st Qu.:3550   male  :168   1st Qu.:2007  
 Median :197.0     Median :4050   NA's  : 11   Median :2008  
 Mean   :200.9     Mean   :4202                Mean   :2008  
 3rd Qu.:213.0     3rd Qu.:4750                3rd Qu.:2009  
 Max.   :231.0     Max.   :6300                Max.   :2009  
 NA's   :2         NA's   :2                                 
```

Histograms in Base R

```
hist(penguins$body_mass_g)
```



Bar Plots in Base R

The `table()` function applied to a vector shows the number of times each value appears.

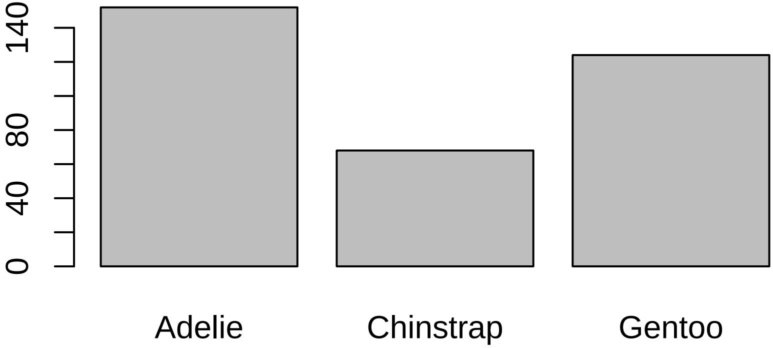
```
table(penguins$species)
```

```
   Adelie Chinstrap    Gentoo 
      152        68       124 
```

We can use a bar plot to visualize these relative frequencies.

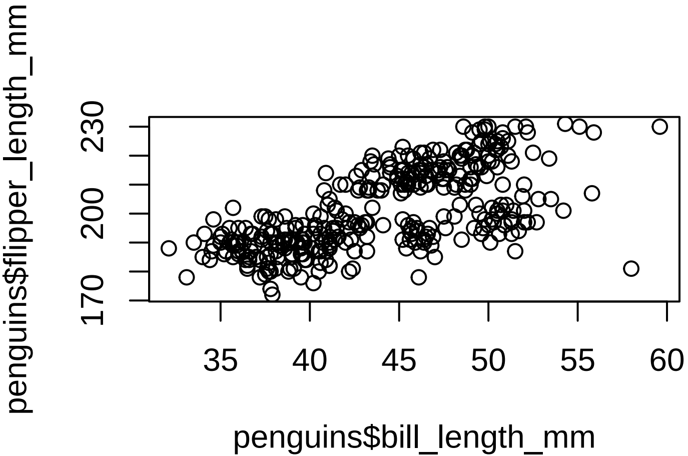
Bar Plots in Base R

```
barplot(table(penguins$species))
```



Scatter Plots in Base R

```
plot(penguins$bill_length_mm, penguins$flipper_length_mm)
```



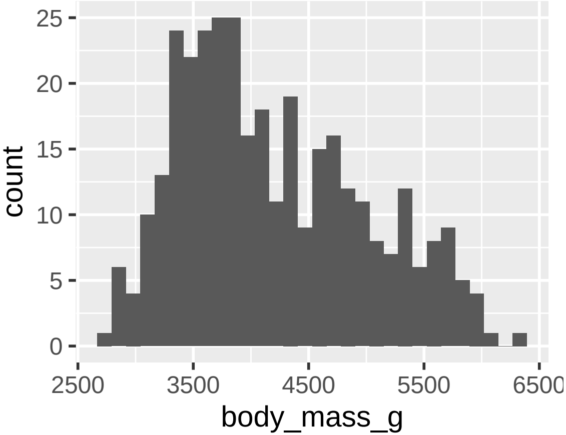
`ggplot`: The Grammar of Graphics

- Although it's possible to customize the plots from base R, we will instead learn how to produce nicer plots using the `ggplot2` package.
- The "gg" in `ggplot` stands for "Grammar of Graphics", which is a scheme to *layer* elements in a plot.
- With the `ggplot2` package, we create plots by adding *layers*.
- Install and load the `ggplot2` package:

```
install.packages("ggplot2")
library(ggplot2)
```

Basic Histogram:

```
ggplot(penguins, aes(body_mass_g)) +
  geom_histogram()
```



Customizing Histograms

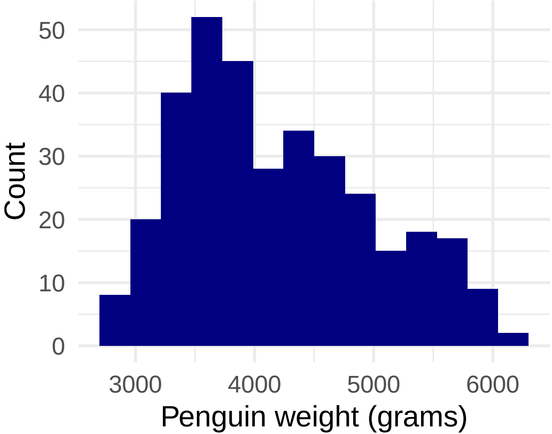
We can customize this with options and by adding *layers*:

- Choosing the number of bins.
- Changing the color of the bins.
- Specifying the axis labels.
- Changing the plot theme (`theme_minimal()` for removing the background colors).

```
ggplot(penguins, aes(body_mass_g)) +
  geom_histogram(bins = 15, fill = "navy") +
  xlab("Penguin weight (grams)") +
  ylab("Count") +
  theme_minimal()
```

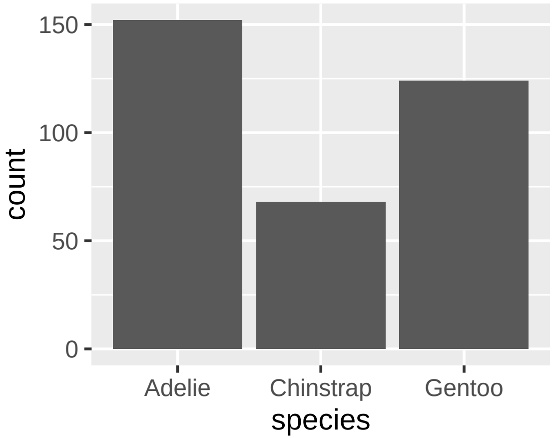
(Output on the next slide)

Customizing Histograms



Basic Bar Plot

```
ggplot(penguins, aes(species)) +
  geom_bar()
```



Cross-Tabulation

- We can also create a bar plot with a cross-tabulation.
- When we put 2 variables x and y in the table( ) function with `table(x, y)`, it shows us how often each combination of the values in x and y appear together in the data:

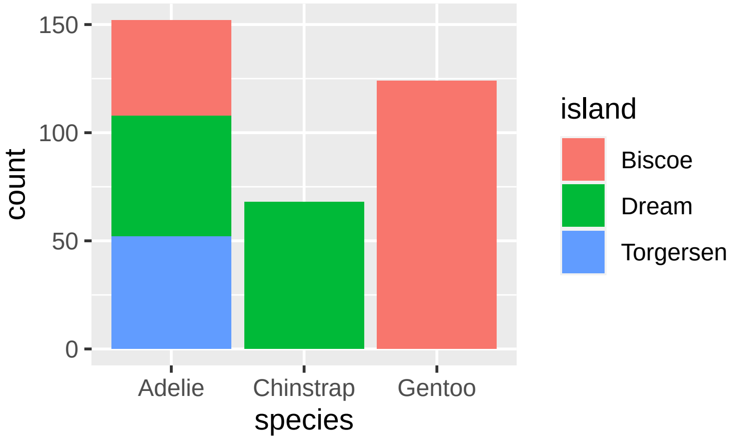
```
table(penguins$species, penguins$island)
```

```
            Biscoe Dream Torgersen
  Adelie        44    56        52
  Chinstrap      0    68         0
  Gentoo       124     0         0
```

- Adelie penguins appear on all 3 islands.
- Chinstrap penguins appear only on Dream island.
- Gentoo penguins appear only on Biscoe island.

Basic Bar Plot with Cross-Tabulation

```
ggplot(penguins, aes(species, fill = island)) +
  geom_bar()
```



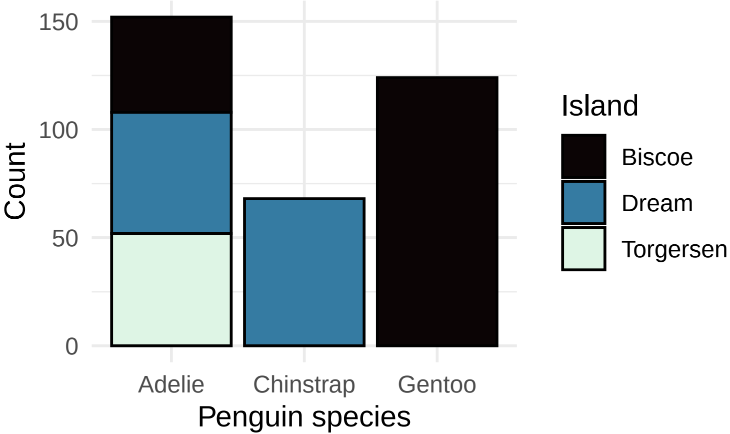
Customizing Bar Plots

- We can change the name of the legend and the "fill" colors using the `scale_fill_discrete()` option.
- We can also specify colors with their *hexidecimal format* instead of color names.
  - We can find the hexidecimal format of a color using any color picker tool.

```
ggplot(penguins, aes(species, fill = island)) +
  geom_bar(color = "black") +
  xlab("Penguin species") +
  ylab("Count") +
  scale_fill_discrete(name = "Island",
                      type = c("#0B0405", "#357BA2", "#DEF5E5")) +
  theme_minimal()
```

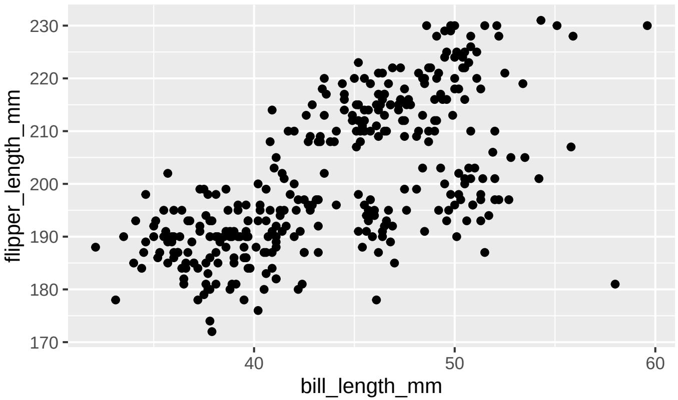
(Output on the next slide)

Customizing Bar Plots



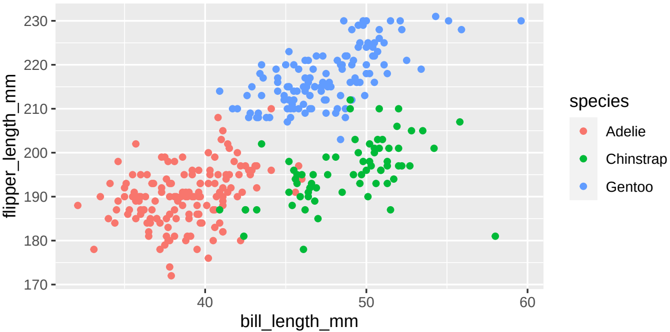
Basic Scatter Plots

```
ggplot(penguins, aes(bill_length_mm, flipper_length_mm)) +
  geom_point()
```



Different Colors for Different Categories

```
ggplot(penguins, aes(bill_length_mm, flipper_length_mm, color = species))
  geom_point()
```

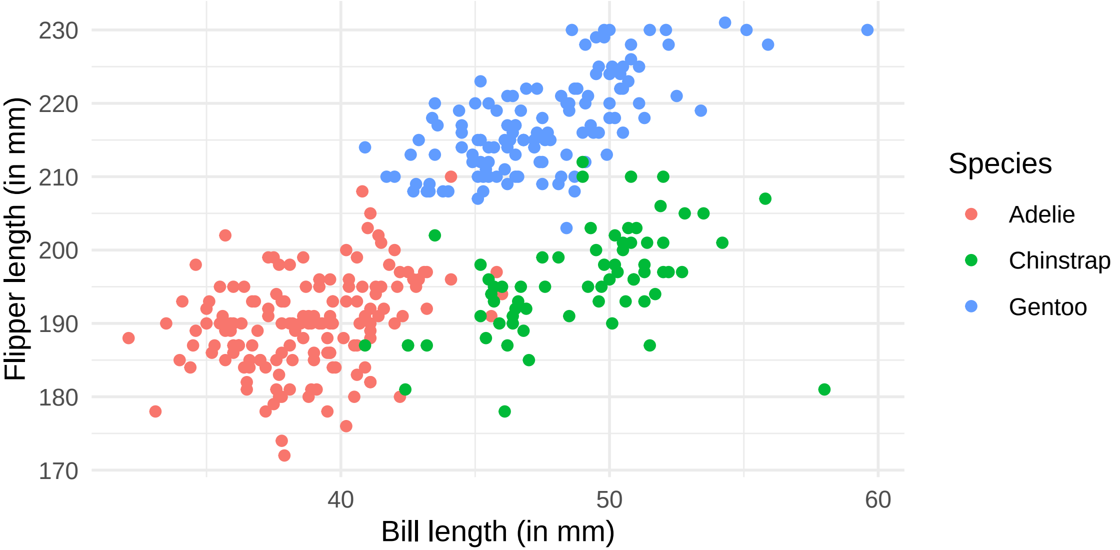


Customizing Scatter Plots

```
ggplot(penguins, aes(bill_length_mm, flipper_length_mm, color = species))
  geom_point() +
  scale_color_discrete(name = "Species") +
  xlab("Bill length (in mm)") +
  ylab("Flipper length (in mm)") +
  theme_minimal()
```

(Output on the next slide)

Customizing Scatter Plots



Making your own R Functions

- It's very easy to create your own R functions.
- Consider the quadratic function:

$$f(x) = -8 - 2x + x^2$$

- We can create an R function, which we call `f()`, to calculate the output of this function as follows:

```
f <- function(x) {
  y <- -8 - 2 * x + x^2
  return(y)
}
```

Making your own R Functions

- We can then use this custom function like we would any other R function.
- The function evaluated at $x = 2$ should equal:

$$f(2) = -8 - 2 \times (2) + (2)^2 = -8 - 4 + 4 = -8$$

- We can check that our custom function gets the same answer:

```
f(2)
```

```
[1] -8
```

- We can also pass vectors into our custom function:

```
f(c(2, 3, 4))
```

```
[1] -8 -5  0
```

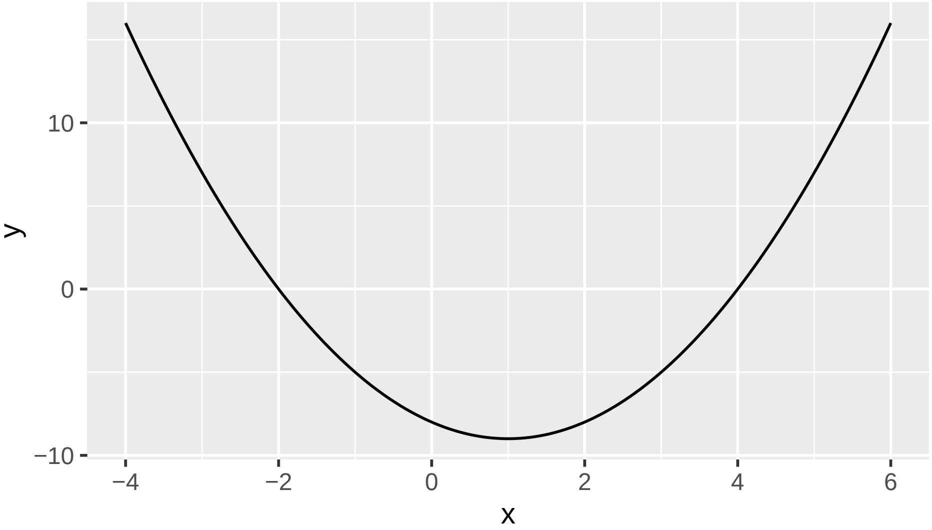
Plotting Functions with ggplot.

- We can also plot custom functions like this with `ggplot`.
- We first choose a range of values of x for which we want to plot the function.
- We then create a sequence of values of x in this range.
- We then evaluate the function at each of these x values to get y.
- We then put these x and y values in a `data.frame` and plot it with `ggplot`.

```r
library(ggplot2)
x <- seq(from = -4, to = 6, length.out = 200)
y <- f(x)
df <- data.frame(x, y)
ggplot(df, aes(x, y)) + geom_line()
```

- Sometimes we don't know what range of x to choose. In this case it's good to pick some values, make the plot, and then adjust the values and make the plot again.

Plotting Functions with `ggplot`.



Univariate Unconstrained Optimization

- When we plotted the function $f(x) = -8 - 2x + x^2$, we saw that it achieved a minimum at $x = 1$.
- We could solve for the minimum analytically by setting the first derivative of the function to zero:

$$\frac{df(x)}{dx} = -2 + 2x = 0 \qquad \Rightarrow \qquad x = 1$$

- We can also use R to find the minimum of the function using the `optimize()` function.

The `optimize()` Function

- We need to specify an interval (lower bound and upper bound) to search for the extreme point.
- We also need to specify if we want a maximum or a minimum using the `maximum` option.

```
optimize(f, interval = c(-100, 100), maximum = FALSE)
```

```
$minimum
[1] 1

$objective
[1] -9
```

- The `optimize()` function finds a minimum at 1, and the function takes a value of -9 at the minimum, i.e. $f(1) = -9$
- If we instead wanted to find the maximum of a function, we would specify `maximum = TRUE`.

The `optimize()` Function

- The output of the `optimize()` function is a `list`.
- If we assign the output to an object called `f_min`, we can extract the minimum with `f_min$minimum`.
  - The $ extraction operator works for lists just like with dataframes.
- We can similarly get the value of the function at the minimum with `f_min$objective`.

```
f_min <- optimize(f, interval = c(-100, 100), maximum = FALSE)
f_min$minimum
```

```
[1] 1
```

```
f_min$objective
```

```
[1] -9
```

Conditional Statements ("If-else")

- Very often we to perform different actions depending on whether something is true or not.
- For this we use *if-else statements*, which also called *conditional statements*.
- The absolute value function is a simple example of this:

$$|x| = \begin{cases} -x & x < 0 \\ x & \text{otherwise} \end{cases}$$

- We ask, "is $x < 0$?". If yes, then return $-x$. If not, then return x.
- Of course, we can always use the `abs()` function in R to calculate the absolute value. But let's create our own function doing exactly this.

Custom absolute value function

```
my_abs <- function(x) {
  if (x < 0) {
    return(-x)
  } else {
    return(x)
  }
}
my_abs(-2)
```

```
[1] 2
```

```
my_abs(3)
```

```
[1] 3
```

If-Else Statements for Vectors

- The previous function we wrote only works with scalars (vectors of length 1).
- If we would try to do `my_abs(c(-2, 3))`, we would get an error.
- To do if-else statements with vectors, we can use the `ifelse()` function.
- The `ifelse()` function takes 3 arguments:
  1. A logical vector (such as testing the condition $x < 0$).
  2. What to return if TRUE (i.e. if $x < 0$).
  3. What to return if FALSE (i.e. if $x \geq 0$).

```r
x <- -5:5
x
```

```
 [1] -5 -4 -3 -2 -1  0  1  2  3  4  5
```

```r
ifelse(x < 0, -x, x)
```

```
 [1] 5 4 3 2 1 0 1 2 3 4 5
```

“If-Else If-Else” Statements

- Sometimes there can be more than 2 cases to test.
- For example, consider the following function which gives the “sign” in front of a number:

$$sgn(x) = \begin{cases} -1 & \text{if } x < 0 \\ 0 & \text{if } x = 0 \\ +1 & \text{otherwise} \end{cases}$$

- For example, $sgn(-2) = -1$, $sgn(0) = 0$, and $sgn(3) = 1$.
- We can code a function in R to do this by nesting if-else statements.

“If-Else If-Else” Statements

```
sgn <- function(x) {
  if (x < 0) {
    return(-1)
  } else if (x == 0) {
    return(0)
  } else {
    return(+1)
  }
}
sgn(-2)
```

```
[1] -1
```

```
sgn(3)
```

```
[1] 1
```

“If-Else If-Else” Statements with Vectors

We can also nest the `ifelse()` function inside of itself to get the sign of a vector of numbers:

```
x <- -3:3
x
```

```
[1] -3 -2 -1  0  1  2  3
```

```
ifelse(x < 0, -1, ifelse(x == 0, 0, 1))
```

```
[1] -1 -1 -1  0  1  1  1
```

Merging

- Merging (or joining) is the R equivalent of the VLOOKUP function in Excel.
- When two datasets have a common ID variable linking them together, we can merge them.
- For example:
  - One dataset with total sales on each day, and another dataset with the temperature on each day. We can link the datasets using the date.
  - One dataset with the total sales in each municipality over a year, and another with the demographic characteristics of each municipality. We can link the datasets using the municipality name.

Merging Example

- We will show a merging example using 2 datasets:
  1. Average daily petrol prices from 2014-2022.
  2. Brent crude oil spot prices from 1987-2022 (excludes weekends and holidays).
- We will merge the datasets by date.

Data Cleaning: Average Daily Petrol Price Data

```
df1 <- read.csv("avg_daily_petrol_prices.csv")
head(df1$date)
```

```
[1] "2014-06-08" "2014-06-09" "2014-06-10" "2014-06-11" "2014-06-12"
[6] "2014-06-13"
```

```
df1$date <- as.Date(df1$date, format = "%Y-%m-%d")
summary(df1)
```

```
      date                  e5              e10            diesel
 Min.   :2014-06-08   Min.   :1.159   Min.   :1.130   Min.   :0.9558
 1st Qu.:2016-07-03   1st Qu.:1.340   1st Qu.:1.318   1st Qu.:1.1322
 Median :2018-07-29   Median :1.402   Median :1.379   Median :1.2353
 Mean   :2018-07-29   Mean   :1.456   Mean   :1.423   Mean   :1.2811
 3rd Qu.:2020-08-23   3rd Qu.:1.522   3rd Qu.:1.479   3rd Qu.:1.3217
 Max.   :2022-09-18   Max.   :2.261   Max.   :2.203   Max.   :2.3343
```

Data Cleaning: Brent Crude Oil Spot Price Data

```
df2 <- read.csv("Europe_Brent_Spot_Price_FOB.csv", skip = 4)
head(df2$Day)
```

```
[1] "09/19/2022" "09/16/2022" "09/15/2022" "09/14/2022" "09/13/2022"
[6] "09/12/2022"
```

```
df2$Day <- as.Date(df2$Day, format = "%m/%d/%Y")
names(df2) <- c("date", "crude_oil")
summary(df2)
```

```
      date              crude_oil    
 Min.   :1987-05-20   Min.   :  9.10  
 1st Qu.:1996-03-06   1st Qu.: 19.03  
 Median :2005-01-04   Median : 38.08  
 Mean   :2005-01-12   Mean   : 48.22  
 3rd Qu.:2013-11-24   3rd Qu.: 69.67  
```

The merge( ) Command:

```
df <- merge(df1, df2, by = "date")
```

```
summary(df)
```

```
      date                  e5              e10             diesel      
 Min.   :2014-06-09   Min.   :1.159   Min.   :1.130   Min.   :0.9558  
 1st Qu.:2016-07-04   1st Qu.:1.339   1st Qu.:1.318   1st Qu.:1.1302  
 Median :2018-07-26   Median :1.402   Median :1.379   Median :1.2345  
 Mean   :2018-07-27   Mean   :1.455   Mean   :1.422   Mean   :1.2797  
 3rd Qu.:2020-08-19   3rd Qu.:1.521   3rd Qu.:1.478   3rd Qu.:1.3216  
 Max.   :2022-09-16   Max.   :2.261   Max.   :2.203   Max.   :2.3343  
   crude_oil     
 Min.   :  9.12  
 1st Qu.: 48.54  
 Median : 61.18  
 Mean   : 63.47  
 3rd Qu.: 72.97  
 Max.   :133.18  
```

Merging: Dropped Observations

- The merged dataset only includes observations where there is a match.
- Observations where there is no corresponding match are dropped:

```
nrow(df1)
```

```
[1] 3025
```

```
nrow(df2)
```

```
[1] 8970
```

```
nrow(df)
```

```
[1] 2107
```

- To avoid dropping rows, we can use the `all.x = TRUE` and/or `all.y = TRUE` options.

Merging with `all.x = TRUE`

- `all.x = TRUE` : Keeps all observations in the 1st dataset, but only merges data from the 2nd dataset when there is a match. When there is no match, variables in the 2nd dataset get assigned NA values.
- `all.y = TRUE` : Keeps all observations in the 2nd dataset, but only merges data from the 1st dataset when there is a match. When there is no match, variables in the 1st dataset get assigned NA values.
- `all = TRUE` : This keeps all observations from both datasets, and variables get assigned NA values when there is no match. This is equivalent to setting both `all.x = TRUE` and `all.y = TRUE`.

Merging with `all.x = TRUE`

```r
df <- merge(df1, df2, by = "date", all.x = TRUE)
```

```r
summary(df)
```

```
      date                  e5             e10            diesel      
 Min.   :2014-06-08   Min.   :1.159   Min.   :1.130   Min.   :0.9558  
 1st Qu.:2016-07-03   1st Qu.:1.340   1st Qu.:1.318   1st Qu.:1.1322  
 Median :2018-07-29   Median :1.402   Median :1.379   Median :1.2353  
 Mean   :2018-07-29   Mean   :1.456   Mean   :1.423   Mean   :1.2811  
 3rd Qu.:2020-08-23   3rd Qu.:1.522   3rd Qu.:1.479   3rd Qu.:1.3217  
 Max.   :2022-09-18   Max.   :2.261   Max.   :2.203   Max.   :2.3343  
                                                                      
   crude_oil     
 Min.   :  9.12  
 1st Qu.: 48.54  
 Median : 61.18  
 Mean   : 63.47  
 3rd Qu.: 72.97  
 Max.   :133.18  
 NA's   :918     
```

Further Remarks on Merging

- If merging on multiple variables, use `by = c("var1", "var2")`.
- If merging variables differ in `df1` and `df2`, use `by.x` and `by.y` instead of `by`. For example:

```
df <- merge(df1, df2, by.x = c("market_area", "date"),
            by.y = c("market", "date"))
```

- To avoid sorting the data, use option `sort = FALSE`.

Reshaping

Suppose you have a dataset structured like this (long format):

```
  id variable value
1  1        x     3
2  1        y     5
3  2        x     4
4  2        y     8
5  3        x     3
6  3        y     1
```

And you wanted to *reshape* it to look like this (wide format):

```
  id x y
1  1 3 5
2  2 4 8
3  3 3 1
```

Reshaping

- Base R has a function that can do this called `reshape()`, but it's not very easy to use.
- The package `reshape2` contains functions to make it easy to go from long to wide format and vice-versa:
  - `dcast(df, id ~ variable)`: long to wide format.
  - `melt(df, idvars = "id")`: wide to long format.

Reshaping: Long to Wide

```r
long <- data.frame(
  id       = rep(1:3, each = 2),
  variable = rep(c("x", "y"), times = 3),
  value    = c(3, 5, 4, 8, 3, 1)
)
library(reshape2)
wide <- dcast(long, id ~ variable)
wide
```

```
  id x y
1  1 3 5
2  2 4 8
3  3 3 1
```

Reshaping: Wide to Long

```r
melt(wide, id.vars = "id")
```

```
  id variable value
1  1        x     3
2  2        x     4
3  3        x     3
4  1        y     5
5  2        y     8
6  3        y     1
```

Overlay Line Plots with ggplot

To overlay line plots with ggplot we need our data in long format.

```r
df <- read.csv("avg_daily_petrol_prices.csv")
df$date <- as.Date(df$date, format = "%Y-%m-%d")
head(df, n = 2)
```

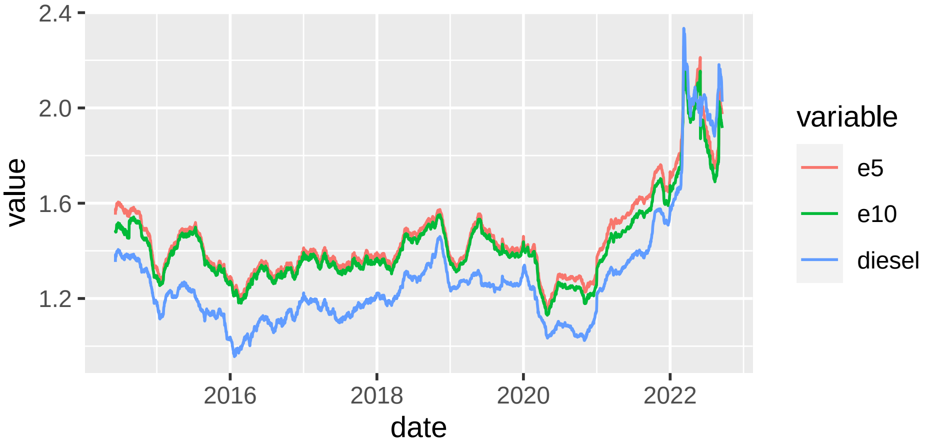
```
        date       e5      e10   diesel
1 2014-06-08 1.551987 1.477774 1.353583
2 2014-06-09 1.576623 1.483362 1.385182
```

```r
df2 <- melt(df, id.vars = "date")
head(df2, n = 2)
```

```
        date variable    value
1 2014-06-08       e5 1.551987
2 2014-06-09       e5 1.576623
```

Overlay Line Plots with ggplot

```
ggplot(df2, aes(date, value, color = variable)) + geom_line()
```

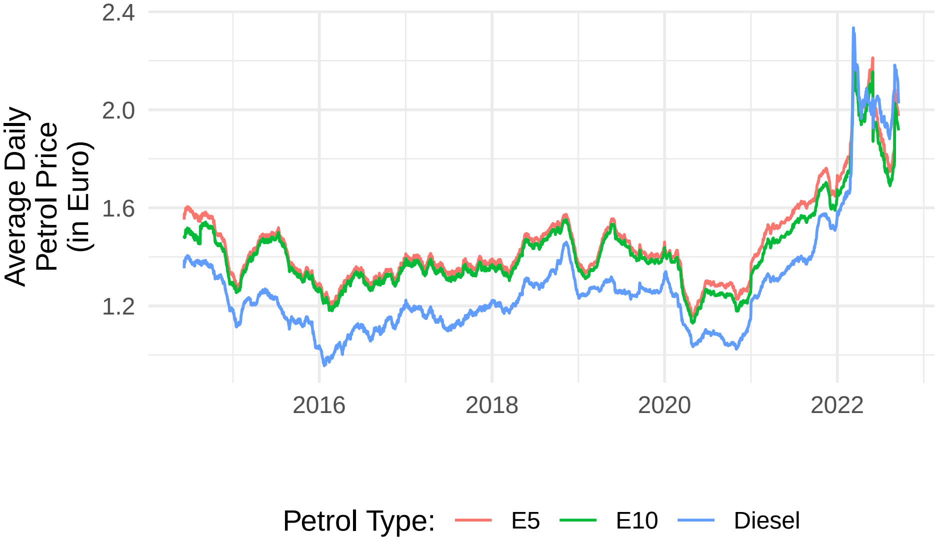


Customizing the Plot

```
levels(df2$variable) <- c("E5", "E10", "Diesel")
library(ggplot2)
ggplot(df2, aes(date, value, color = variable)) +
  geom_line() +
  xlab("") +
  ylab("Average Daily\nPetrol Price\n(in Euro)") +
  scale_color_discrete(name = "Petrol Type:") +
  theme_minimal() +
  theme(legend.direction = "horizontal",
        legend.position = "bottom")
```

(Output on next slide)

Customizing the Plot



Aggregating by Group

- If we want to get the sum or average by group we can use the `aggregate()` function.
- The `aggregate()` function is a bit like the R version of pivot tables in Excel.
- If we want to get the average of `x` by group `g` in the dataframe `df`, we use:

```
aggregate(x ~ g, FUN = mean, data = df)
```

- We'll show this using the petrol price data as an example.

Average Price of E5 Petrol by Year

```
df <- read.csv("avg_daily_petrol_prices.csv")
df$date <- as.Date(df$date, format = "%Y-%m-%d")
library(lubridate)
df$year <- year(df$date)
aggregate(e5 ~ year, FUN = mean, data = df)
```

```
  year       e5
1 2014 1.519195
2 2015 1.393170
3 2016 1.302767
4 2017 1.368414
5 2018 1.454098
6 2019 1.430592
7 2020 1.288080
8 2021 1.579992
9 2022 1.933512
```

Maximum Price of E5 by Year

```r
aggregate(e5 ~ year, FUN = max, data = df)
```

```
  year       e5
1 2014 1.605252
2 2015 1.519229
3 2016 1.395620
4 2017 1.414228
5 2018 1.573760
6 2019 1.555623
7 2020 1.461060
8 2021 1.761985
9 2022 2.260581
```

Average Price of E5 and E10 by Year

```r
aggregate(cbind(e5, e10) ~ year, FUN = mean, data = df)
```

```
  year       e5      e10
1 2014 1.519195 1.461632
2 2015 1.393170 1.373425
3 2016 1.302767 1.282375
4 2017 1.368414 1.345430
5 2018 1.454098 1.430955
6 2019 1.430592 1.408177
7 2020 1.288080 1.253603
8 2021 1.579992 1.522833
9 2022 1.933512 1.875897
```

Average Price of All Variables by Year

```r
aggregate(. ~ year, FUN = mean, data = df)
```

```
  year    date       e5      e10   diesel
1 2014 16332.0 1.519195 1.461632 1.334612
2 2015 16618.0 1.393170 1.373425 1.173013
3 2016 16983.5 1.302767 1.282375 1.081282
4 2017 17349.0 1.368414 1.345430 1.161306
5 2018 17714.0 1.454098 1.430955 1.287264
6 2019 18079.0 1.430592 1.408177 1.265341
7 2020 18444.5 1.288080 1.253603 1.111068
8 2021 18810.0 1.579992 1.522833 1.387114
9 2022 19123.0 1.933512 1.875897 1.941386
```