Learning R by doing, oriented to actuaries and risk managers

Hands-on webinar

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Prologue

Introduction

Course

https://github.com/katrienantonio/werkt-U-al-met-R

The course repo on GitHub, where you can find the data sets, lecture sheets and R scripts.

Us

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Checklist

☑ Do you have a fairly recent version of R?

```
version$version.string
## [1] "R version 4.0.3 (2020-10-10)"
```

☑ Do you have a fairly recent version of RStudio?

```
RStudio.Version()$version
## Requires an interactive session but should return something like "[1] '1.3.1093'"
```

☑ Have you installed the R packages listed in the software requirements?

or

☑ Have you created an account on RStudio Cloud (to avoid any local installation issues)?

Why this session?

The goals of this session

- explore the R universe
- discover different data and object types and syntax
- work with data: import, visualization, wrangling
- write your own functions
- learn by doing, get you started (in particular when you have limited experience in R).

> *"In short, we will cover things that we wish someone had taught us in our undergraduate programs."*
>
> This quote is from the Data science for economists course by Grant McDermott.

What is R?

> The R environment is an integrated suite of software facilities for data manipulation, calculation and graphical display.

A brief history:

- R is a dialect of the S language.
- R was written by Robert Gentleman and Ross Ihaka in 1992.
- The R source code was first released in 1995.
- In 1998, the Comprehensive R Archive Network CRAN was established.
- The first official release, R version 1.0.0, dates to 2000-02-29. Currently R 4.0.3 (October, 2020).
- R is open source via the GNU General Public License.

Explore the R architecture

- R is like a car's engine
- RStudio is like a car's dashboard, an integrated development environment (IDE) for R.

R: Engine	RStudio: Dashboard
	

How do I code in R?

Keep in mind:

- unlike other software like Excel, STATA, or SAS, R is an interpreted language
- no point and click in R!
- you have to program in R!

R packages extend the functionality of R by providing additional functions, and can be downloaded for free from the internet.

R: A new phone	R Packages: Apps you can download
	GET IT ON Google Play Download on the App Store

How to install and load an R package?

Install the {ggplot2} package for data visualisation

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

Load the installed package

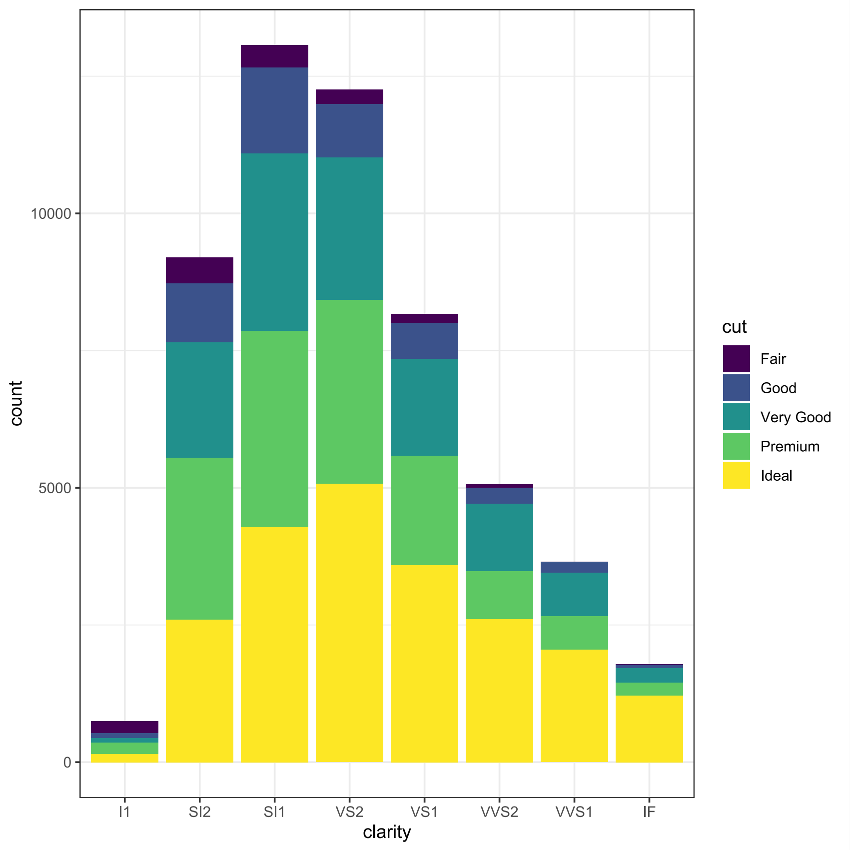
```
library(ggplot2)
```

And give it a try

```
head(diamonds)
ggplot(diamonds, aes(clarity, fill = cut)) +
  geom_bar() + theme_bw()
```

Packages are developed and maintained by R users worldwide.

They are shared with the R community through CRAN: now 16,744 packages online (on November 30, 2020)!



Workflow of a data scientist

Here is a model of the **tools needed in a typical data science project**:

> Together, tidying and transforming are called **wrangling**, because getting your data in a form that's natural to work with often feels like a fight!
>
> Models are complementary tools to visualisation. Once you have made your questions sufficiently precise, you can use a model to answer them. Models are a fundamentally **mathematical or computational tool**, so they generally scale well. But every model makes **assumptions**, and by its very nature a model cannot question its own assumptions. That means **a model cannot fundamentally surprise you**.

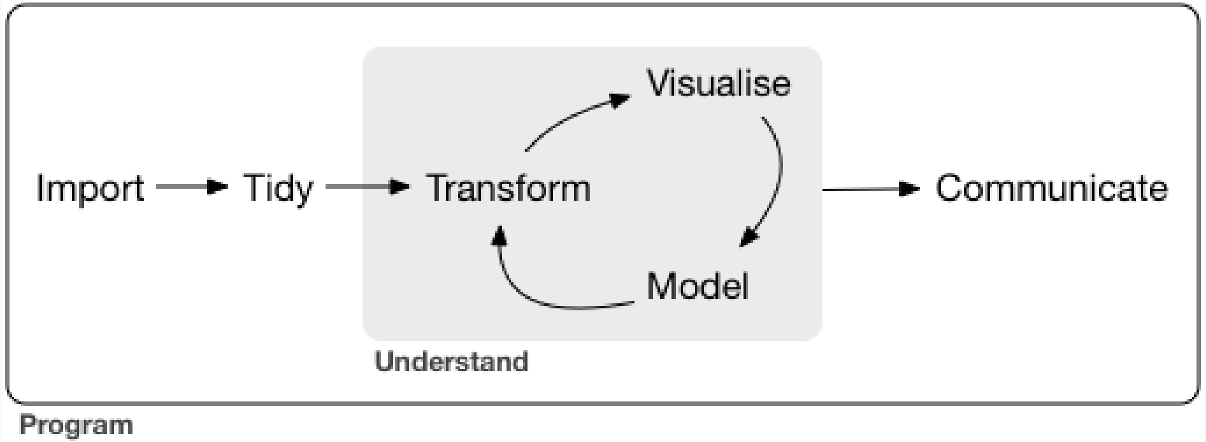
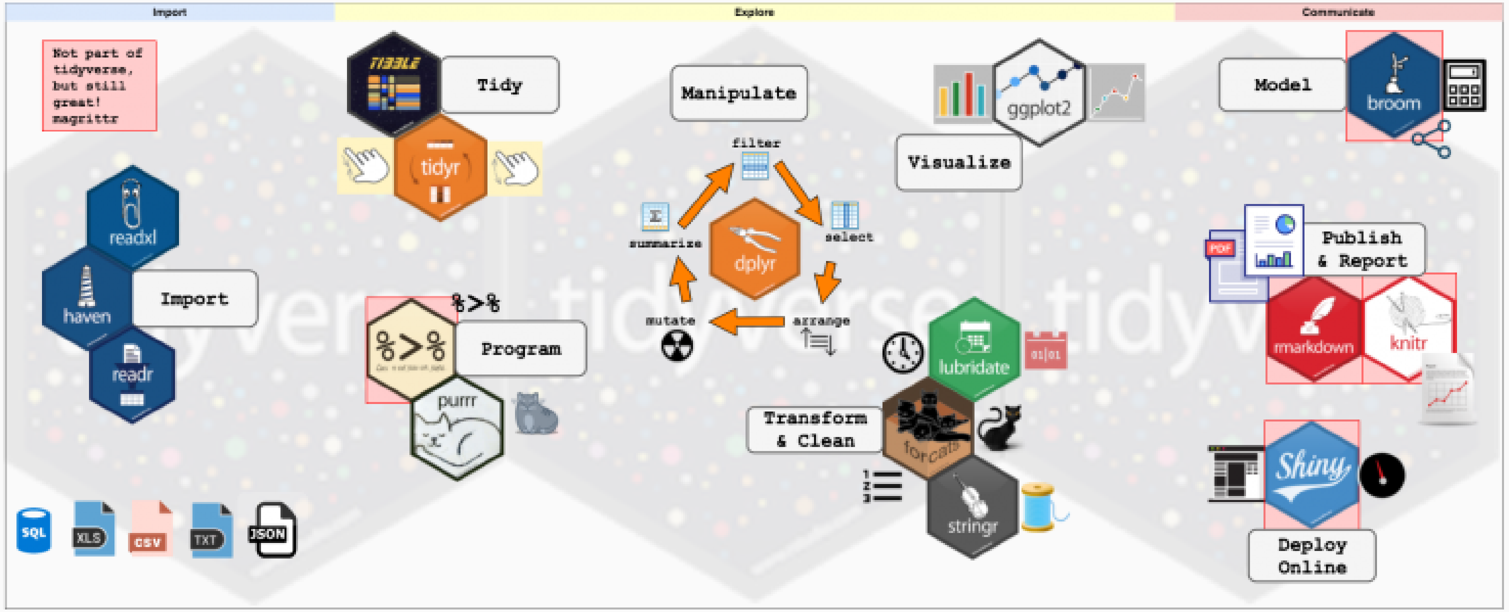


Figure and quote taken from Chapter 1 in R for data science.

Welcome to the tidyverse!

> The **tidyverse** is an opinionated collection of R packages designed for data science. All packages share an underlying design philosophy, grammar, and data structures.



More on: tidyverse.

Install the packages with `install.packages("tidyverse")`. Then run `library(tidyverse)` to load the core tidyverse.

Today's Outline

- Prologue
- R syntax, object and data types
  - little arithmetics
  - variables and data types
  - basic data structures
- Working with data in R
  - data paths and read.table
  - import data with {readr}, {readxl} and {haven}
  - exploratory data analysis
  - data wrangling in the tidyverse
  - the pipe operator `%>%`
  - tidy manipulation with {dplyr}
- More on data visualization in R
  - advanced plots with {ggplot2}
- Conditionals and control flow
  - relational and logical operators
  - conditionals and loops
- Writing functions

R syntax, object and data types

R style guide

Deciding on a **programming style** provides consistency to your code and assists in reading and writing code.

The choice of style guide is unimportant, but it is important to choose a style!

This workshop follows a set of rules roughly based on the tidyverse style guide.

R style guide (cont.)

Variable names contain only **lower case** letters. If the name consists of multiple words, then these words are separated by **underscores**.

```
number_of_simulations <- 100
```

User defined functions follow the same convention as variable names, but start with a **capital** letter.

```
Multiply_by_2 <- function(x) {
  return(x * 2)
}
```

Functions from external packages usually start with a lowercase letter.

```
zero_list <- rep(0, 100)
```

R as a calculator

Do little arithmetics with R:

- write R code in the console
- every line of code is interpreted and executed by R
- you get a message whether or not your code was correct
- the output of your R code is then shown in the console
- use # sign to add comments, like Twitter!

Now run in the console

```
10^2 + 36
[1] 136
```

You asked and R answered!

Variables

A basic concept in (statistical) programming is a **variable**.

- a variable allows you to store a value (e.g. 4) or an object (e.g. a function description) in R
- use this variable's name to easily access the value or the object that is stored within this variable.

Assign value `4` to variable `a`

```
a <- 4
```

and verify the variable stored

```
a
[1] 4
```

Your turn

Verify the following instructions:

```
a*5
(a+10)/2
a ← a+1
print(a)
```

Data types

R works with numerous **data types**: e.g.

- decimal values like 4.5 are called **numerics**
- natural numbers like 4 are called **integers**
- Boolean values (`TRUE` or `FALSE`) are called **logical**
- `Date` or `POSIXct` for time based variables[1]; `Date` stores just a date and `POSIXct` stores a date and time
- text (or string) values are called **characters**.

[1] Both objects are actually represented as the number of days (`Date`) or seconds (`POSIXct`) since January 1, 1970.

Your turn

Run the following instructions and pay attention to the code:

```
my_numeric <- 42.5

my_character <- "some text"

my_logical <- TRUE

my_date <- as.Date("06/17/2019", "%m/%d/%Y")
```

Verify the data type of a variable with the `class()` function: e.g.

```
class(my_numeric)
[1] "numeric"
class(my_date)
[1] "Date"
```

Everything is an object

> The fundamental design principle underlying R is “everything is an object”.

Keep in mind:

- in R, an analysis is broken down into a series of steps
- intermediate results are stored in objects, with minimal output at each step (often none)
- manipulate the objects to obtain the information required
- a variable in R can take on any available data type, or hold any R object.

Your turn

Run

```r
ls()
```

to list all objects stored in R's memory.

Use `rm()` to remove an object from R's memory, e.g.

```r
rm(a)                                    # remove a single object
ls()                                     # verify that object a is removed
rm(my_character, my_logical)             # remove multiple objects
ls()                                     # which object are we left with?
rm(list = c('my_date', 'my_numeric'))    # remove a list of objects
rm(list = ls())                          # remove all objects
```

Vectors

A **vector** is a simple tool to store data:

- one-dimension arrays that can hold numeric data, character data, or logical data
- you create a vector with the combine function `c()`
- operations are applied to each element of the vector automatically, there is no need to loop through the vector.

Here are some first examples:

```
my_vector <- c(0, 3:5, 20, 0)
my_vector[2]        # inspect entry 2 from vector my_vector
## [1] 3
my_vector[2:3]      # inspect entries 2 and 3
## [1] 3 4
length(my_vector)   # get vector length
## [1] 6
my_family <- c("Katrien", "Jan", "Leen")
my_family
## [1] "Katrien" "Jan"     "Leen"
```

Your turn

You can give a name to the elements of a vector with the `names()` function:

```
my_vector <- c("Katrien Antonio", "teacher")
names(my_vector) <- c("Name", "Profession")
my_vector
             Name        Profession
"Katrien Antonio"         "teacher"
```

Now it's your turn!

Inspect `my_vector` using:

- the `attributes()` function
- the `length()` function
- the `str()` function

Your turn

You can give a name to the elements of a vector with the `names()` function:

```
my_vector <- c("Katrien Antonio", "teacher")
names(my_vector) <- c("Name", "Profession")
my_vector
             Name        Profession
"Katrien Antonio"         "teacher"
```

```
attributes(my_vector)
$names
[1] "Name"       "Profession"

length(my_vector)
[1] 2

str(my_vector)
 Named chr [1:2] "Katrien Antonio" "teacher"
 - attr(*, "names")= chr [1:2] "Name" "Profession"
```

Matrices

A **matrix** is:

- a collection of elements of the same data type (numeric, character, or logical)
- fixed number of rows and columns.

A first example

```
my_matrix <- matrix(1:12, 3, 4, byrow = TRUE)
my_matrix
     [,1] [,2] [,3] [,4]
[1,]    1    2    3    4
[2,]    5    6    7    8
[3,]    9   10   11   12
my_matrix[1, 1]
[1] 1
```

Data frames and tibbles

A **data frame**:

- is pretty much the *de facto* data structure for most tabular data
- what we use for statistics
- variables of a data set as columns and the observations as rows.

A **tibble**:

- a.k.a `tbl`
- a type of data frame common in the `tidyverse`
- slightly different default behaviour than data frames.

Let's explore some differences between both structures!

Your turn

Inspect a built-in data frame

```
mtcars
str(mtcars)
head(mtcars)
```

Extract a variable from a data frame and ask a `summary`

```
summary(mtcars$cyl)   # use $ to extract variable from a data frame
```

Now inspect a tibble

```
diamonds
str(diamonds)  # built-in in library ggplot2
head(diamonds)
```

Can you list some differences?

Lists

A list allows you to

- gather a variety of objects under one name in an ordered way
- these objects can be matrices, vectors, data frames, even other lists
- a list is some kind of super data type
- you can store practically any piece of information in it!

A first example of a list:

```
my_list ← list(one = 1, two = c(1, 2), five = seq(1, 4, length = 5), six = c("Katrien", "Jan"))
names(my_list)
[1] "one"  "two"  "five" "six"
str(my_list)
List of 4
 $ one : num 1
 $ two : num [1:2] 1 2
 $ five: num [1:5] 1 1.75 2.5 3.25 4
 $ six : chr [1:2] "Katrien" "Jan"
```

Your turn

1. Create a vector `fav_music` with your favourite artists.
2. Create a vector `num_records` with the number of records you have in your collection of each of those artists.
3. Create a vector `num_concerts` with the number of times you attended a concert of these artists.
4. Put everything together in a data frame, assign the name `my_music` to this data frame and change the labels of the information stored in the columns to `artist`, `records` and `concerts`.
5. Extract the variable `num_records` from the data frame `my_music`.
6. Calculate the total number of records in your collection (for the defined set of artists).
7. Check the structure of the data frame, ask for a `summary`.

My solution for **Q. 1-4**:

```r
fav_music <- c("Prince", "REM", "Ryan Adams", "BLOF")
num_records <- c(2, 7, 5, 1)
num_concerts <- c(0, 3, 1, 0)
my_music <- data.frame(artist = fav_music,
                       records = num_records,
                       concerts = num_concerts)
```

My solution for **Q. 5-7**:

```r
my_music$records
## [1] 2 7 5 1
sum(my_music$records)
## [1] 15
summary(my_music)
##     artist             records        concerts
##  Length:4           Min.   :1.00   Min.   :0.0
##  Class :character   1st Qu.:1.75   1st Qu.:0.0
##  Mode  :character   Median :3.50   Median :0.5
##                     Mean   :3.75   Mean   :1.0
##                     3rd Qu.:5.50   3rd Qu.:1.5
##                     Max.   :7.00   Max.   :3.0
```

Working with data in R

Path to your file

Some useful instructions regarding path names:

- get your working directory

```
getwd()
```

- specify a path name, with forward slash or double back slash, and set your working directory

```
path ← file.path("/Users/roelhenckaerts/Dropbox/Workshop AG")
setwd(path)
```

- use a relative path

```
path_pc ← file.path("./data/PC_data.txt") # single dot represents current directory
```

or

```
path_pc ← file.path("../data/PC_data.txt") # double dot represents parent directory
```

Path to your file (cont.)

Some useful instructions regarding path names:

- extract the directory of the current active file in RStudio via the package `rstudioapi`

```
path <- dirname(rstudioapi::getActiveDocumentContext()$path)
setwd(path)
```

- a more general approach to achieve the same via the package `here`

```
path <- here::here()
setwd(path)
```

- these instructions are recommended because they avoid referring to a specific working directory on your computer
- this allows you (and your colleagues) to get started right away. The only thing you need is an organized file structure.

Import a .txt file

`read.table()` is the most basic importing function with tons of different arguments, see `?read.table`

Let's give this a try:

```
path_secura <- file.path('../data/SecuraRe.txt')
secura_re <- read.table(path_secura, header = TRUE)
str(secura_re)
## 'data.frame':    371 obs. of  2 variables:
##  $ Year: int  1990 1991 1991 1988 1993 1991 1993 1994 1994 1988 ...
##  $ Loss: int  7898639 7487232 7389404 6924749 6685249 5625469 5549253 5342757 5127321 5100022 ...
```

Useful packages for data import

readxl

haven

readr

The readr package

The goal of `readr` is to provide a fast and friendly way to read rectangular data (like csv, tsv, and fwf).

Column specification via `col_types` describes how each column should be converted, but readr will guess it for you automatically.

`readr` supports seven file formats with seven `read_` functions:

- `read_csv()`: comma separated (CSV) files
- `read_tsv()`: tab separated files
- `read_delim()`: general delimited files
- `read_fwf()`: fixed width files
- `read_table()`: tabular files where columns are separated by white-space
- `read_log()`: web log files.

More details on https://readr.tidyverse.org/.

The readxl package

The `readxl` package makes it easy to get Excel data into R:

- no external dependencies, so it's easy to install and use
- designed to work with tabular data.

```
path_urbanpop <- file.path("../data/urbanpop.xlsx")
readxl::excel_sheets(path_urbanpop) # list sheet names with excel_sheets()
## [1] "1960-1966" "1967-1974" "1975-2011"
```

Specify a worksheet by name or number, e.g.

```
pop_1 <- readxl::read_excel(path_urbanpop, sheet = 1)
pop_2 <- readxl::read_excel(path_urbanpop, sheet = "1967-1974")
```

and inspect

```
names(pop_1)
## [1] "country" "1960"    "1961"    "1962"    "1963"    "1964"    "1965"
## [8] "1966"
names(pop_2)
## [1] "country" "1967"    "1968"    "1969"    "1970"    "1971"    "1972"
```

The haven package

The `haven` package enables R to read and write various data formats used by other statistical packages.

It supports:

- **SAS**: `read_sas()` reads .sas7bdat and .sas7bcat files and `read_xpt()` reads SAS transport files (version 5 and version 8). `write_sas()` writes .sas7bdat files.
- **SPSS**: `read_sav()` reads .sav files and `read_por()` reads the older .por files. `write_sav()` writes .sav files.
- **Stata**: `read_dta()` reads .dta files (up to version 15). `write_dta()` writes .dta files (versions 8-15).

Your turn

1. Read the file 'PC_data.txt' in the data folder with the `read.table` function.

2. Experiment with function arguments of `read.table`, for example `header`, `nrows` and `skip`.

An illustration:

```r
path_pc <- file.path('../data/PC_data.txt')
mtpl_base <- read.table(path_pc, header = FALSE, nrow = 100, skip = 10)
str(mtpl_base)
## 'data.frame':	100 obs. of  18 variables:
##  $ V1 : int  10 11 12 13 14 15 16 17 18 19 ...
##  $ V2 : int  0 1 0 0 0 0 0 0 0 0 ...
##  $ V3 : num  0 545 0 0 0 ...
##  $ V4 : num  NA 545 NA NA NA ...
##  $ V5 : num  1 1 0.981 1 0.973 ...
##  $ V6 : chr  "PO" "FO" "TPL" "PO" ...
##  $ V7 : chr  "gasoline" "diesel" "diesel" "gasoline" ...
##  $ V8 : chr  "private" "private" "private" "private" ...
##  $ V9 : chr  "N" "N" "N" "N" ...
##  $ V10: chr  "male" "male" "male" "male" ...
##  $ V11: int  34 39 55 77 49 63 43 51 67 52 ...
##  $ V12: int  7 1 11 9 8 0 1 0 10 0 ...
##  $ V13: int  6 2 6 6 19 7 2 7 6 16 ...
##  $ V14: int  74 85 87 104 71 104 85 113 130 125 ...
##  $ V15: int  1000 1000 1000 1000 1000 1000 1000 1000 1000 1000 ...
##  $ V16: chr  "BRUSSEL" "BRUSSEL" "BRUSSEL" "BRUSSEL" ...
##  $ V17: num  4.36 4.36 4.36 4.36 4.36 ...
##  $ V18: num  50.8 50.8 50.8 50.8 50.8 ...
```

The following code illustrates the use of `col_types` in `readr::read_table` to specify column types:

```
path_pc <- file.path('../data/PC_data.txt')
mtpl_tidy <- readr::read_table2(path_pc, col_types = 'iidddfffffiiiiffdd')
str(mtpl_tidy, give.attr = FALSE)
## tibble [163,231 x 18] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ ID      : int [1:163231] 1 2 3 4 5 6 7 8 9 10 ...
##  $ NCLAIMS : int [1:163231] 1 0 0 0 1 0 1 0 0 0 ...
##  $ AMOUNT  : num [1:163231] 1618 0 0 0 156 ...
##  $ AVG     : num [1:163231] 1618 NA NA NA 156 ...
##  $ EXP     : num [1:163231] 1 1 1 1 0.0466 ...
##  $ COVERAGE: Factor w/ 3 levels "TPL","PO","FO": 1 2 1 1 1 1 3 1 3 2 ...
##  $ FUEL    : Factor w/ 2 levels "gasoline","diesel": 1 1 2 1 1 1 1 1 1 1 ...
##  $ USE     : Factor w/ 2 levels "private","work": 1 1 1 1 1 1 1 1 1 1 ...
##  $ FLEET   : Factor w/ 2 levels "N","Y": 1 1 1 1 1 1 1 1 1 1 ...
##  $ SEX     : Factor w/ 2 levels "male","female": 1 2 1 1 2 1 1 2 1 1 ...
##  $ AGEPH   : int [1:163231] 50 64 60 77 28 26 26 58 59 34 ...
##  $ BM      : int [1:163231] 5 5 0 0 9 11 11 11 0 7 ...
##  $ AGEC    : int [1:163231] 12 3 10 15 7 12 8 14 3 6 ...
##  $ POWER   : int [1:163231] 77 66 70 57 70 70 55 47 98 74 ...
##  $ PC      : Factor w/ 583 levels "1000","1030",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ TOWN    : Factor w/ 578 levels "BRUSSEL","SCHAARBE",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ LONG    : num [1:163231] 4.36 4.36 4.36 4.36 4.36 ...
##  $ LAT     : num [1:163231] 50.8 50.8 50.8 50.8 50.8 ...
```

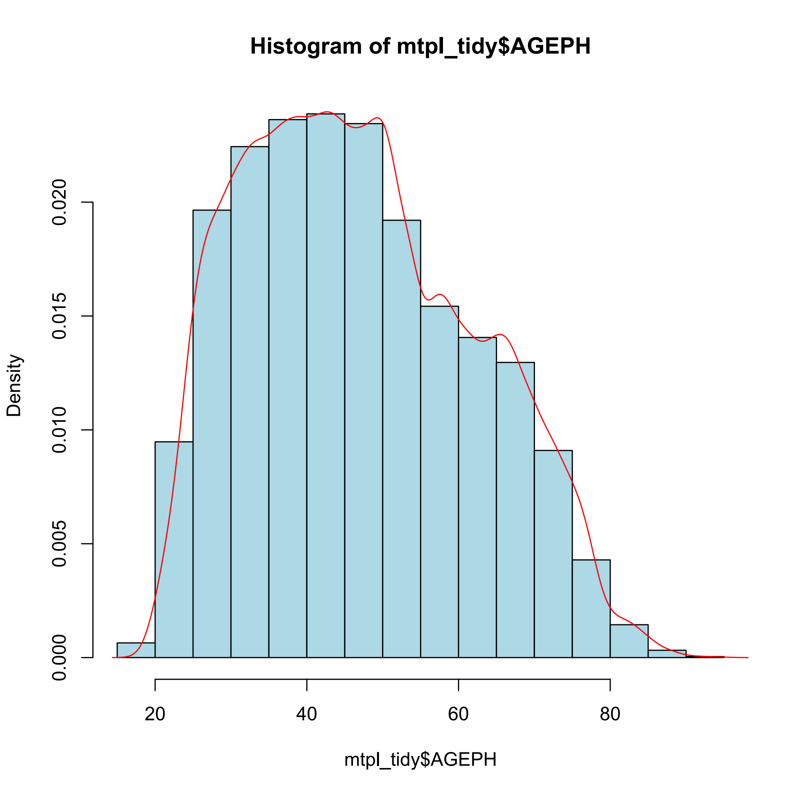
Explore a numeric variable

Explore the **numeric** variable `AGEPH`:

```
# get a summary
summary(mtpl_tidy$AGEPH)
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      18      35      46      47      58      95

# check if variable is numeric
is.numeric(mtpl_tidy$AGEPH)
## [1] TRUE

# get mean
mean(mtpl_tidy$AGEPH)
## [1] 46.99999

# get variance
var(mtpl_tidy$AGEPH)
## [1] 219.9695
```

Visualize the distribution:

```
hist(mtpl_tidy$AGEPH, freq = FALSE,
     nclass = 20, col = "light blue")
lines(density(mtpl_tidy$AGEPH), col = "red")
```



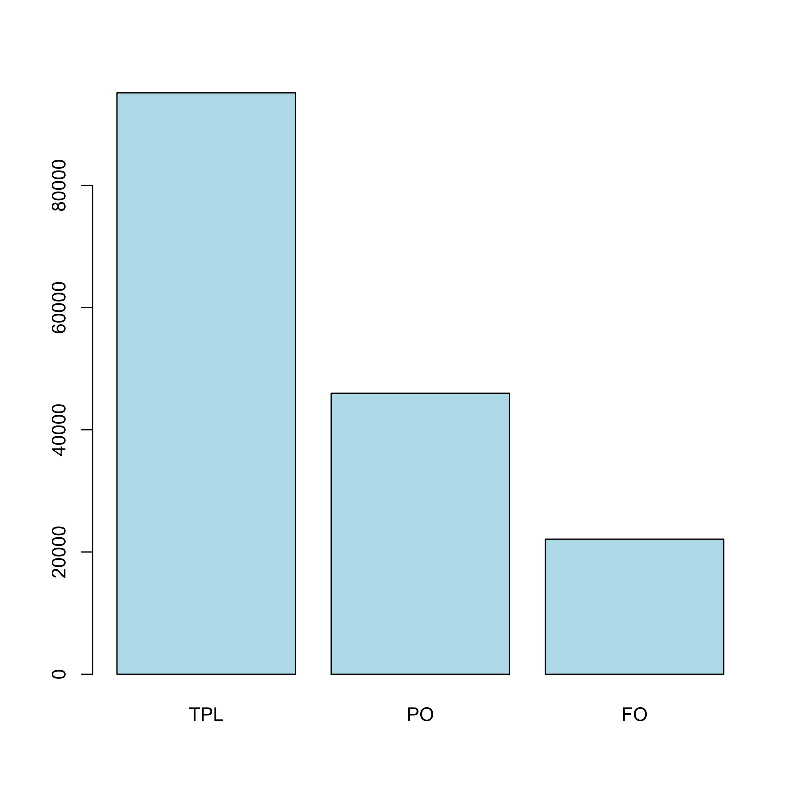
Explore a factor variable

Explore the **factor** variable `COVERAGE`:

```
# check if variable is a factor
is.factor(mtpl_tidy$COVERAGE)
## [1] TRUE

# get observation counts
table(mtpl_tidy$COVERAGE)
##
##   TPL    PO    FO
## 95136 45988 22107

# get proportional observation counts
prop.table(table(mtpl_tidy$COVERAGE))
##
##       TPL        PO        FO
## 0.5828305 0.2817357 0.1354338
```

Visualize the distribution:

```
barplot(table(mtpl_tidy$COVERAGE),
        col = "light blue")
```



Explore two factor variables

Explore the two **factor** variables `SEX` and `FUEL`:

```
table(mtpl_tidy$SEX, mtpl_tidy$FUEL)
##
##          gasoline diesel
##   male      79546  40510
##   female    33287   9888
```

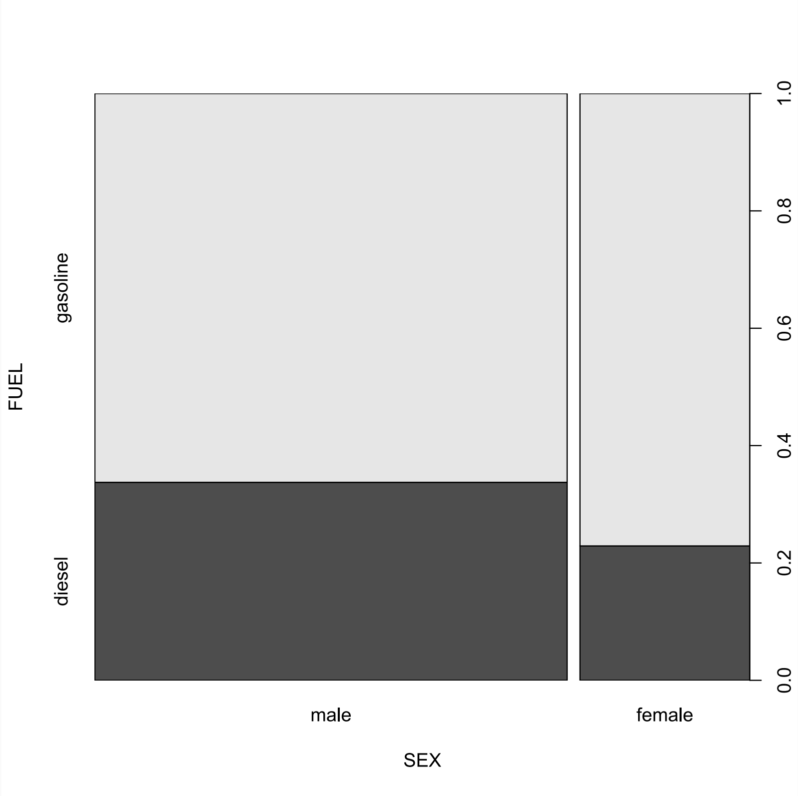
```
prop.table(table(mtpl_tidy$SEX, mtpl_tidy$FUEL))
##
##            gasoline     diesel
##   male   0.48732165 0.24817590
##   female 0.20392572 0.06057673
```

```
prop.table(table(mtpl_tidy$SEX, mtpl_tidy$FUEL), 1)
##
##           gasoline    diesel
##   male   0.6625741 0.3374259
##   female 0.7709786 0.2290214
```

Try `prop.table(table(mtpl_tidy$SEX, mtpl_tidy$FUEL), 2)`

Visualize the distribution:

```
plot(FUEL ~ SEX, data = mtpl_tidy)
```



Explore a factor and a numeric variable

Explore the **numeric** variable `POWER` and the **factor** `SEX`:

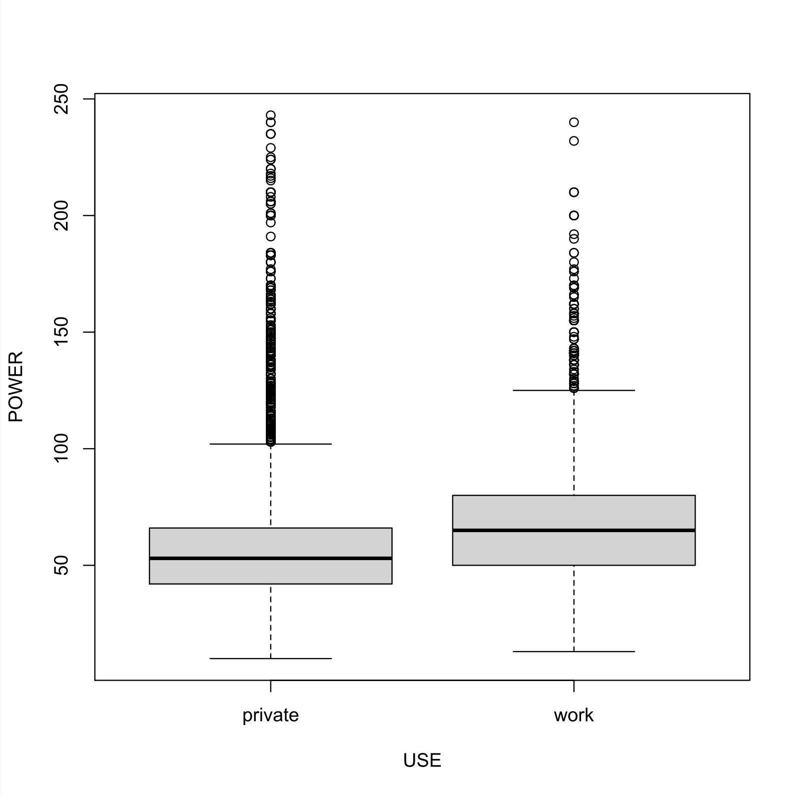
```
tapply(mtpl_tidy$POWER, mtpl_tidy$USE, mean)
##  private     work
## 55.48592 66.21830

tapply(mtpl_tidy$POWER,
       list(mtpl_tidy$USE, mtpl_tidy$FUEL), mean)
##         gasoline   diesel
## private 56.47123 53.20774
## work    69.86773 61.63824
```

`tapply` does the following:

- subsets `POWER` by `USE` (and `FUEL`)
- applies the function `mean` to each subset

Visualize the distribution:

```
boxplot(POWER ~ USE, data = mtpl_tidy)
```



Three directions for data wrangling

Three lines of work are available:

- the basic R instructions (e.g. using `subset`, `aggregate`)
- the RStudio line offering the packages from the {tidyverse}, including the {dplyr} package
- the {data.table} line developed by Matt Dowle, see e.g. DataCamp's course on {data.table}.

The latter two:

- offer advanced, and fast, data handling with large R objects and lots of flexibility
- have a very specific syntax, with a demanding learning curve.

This tutorial will mainly explore the {tidyverse} direction.

The basic split-apply-combine strategy

We first cover some basic R instructions, before diving into the {tidyverse}.

Use the `diamonds` data set (from the `ggplot2` package) and subset

```
subset(diamonds, cut == "Ideal") # rows
diamonds[, c("carat", "cut", "color", "clarity")] # columns
```

Calculate a new variable

```
diamonds$price_per_carat <- diamonds$price/diamonds$carat
```

Calculate average `price` per each type of `cut`

```
aggregate(price ~ cut, diamonds, mean)
```

or

```
aggregate(price ~ cut + color, diamonds, mean)
```

Entering the tidyverse

The tidyverse is a collection of R packages sharing the same design philosphy.

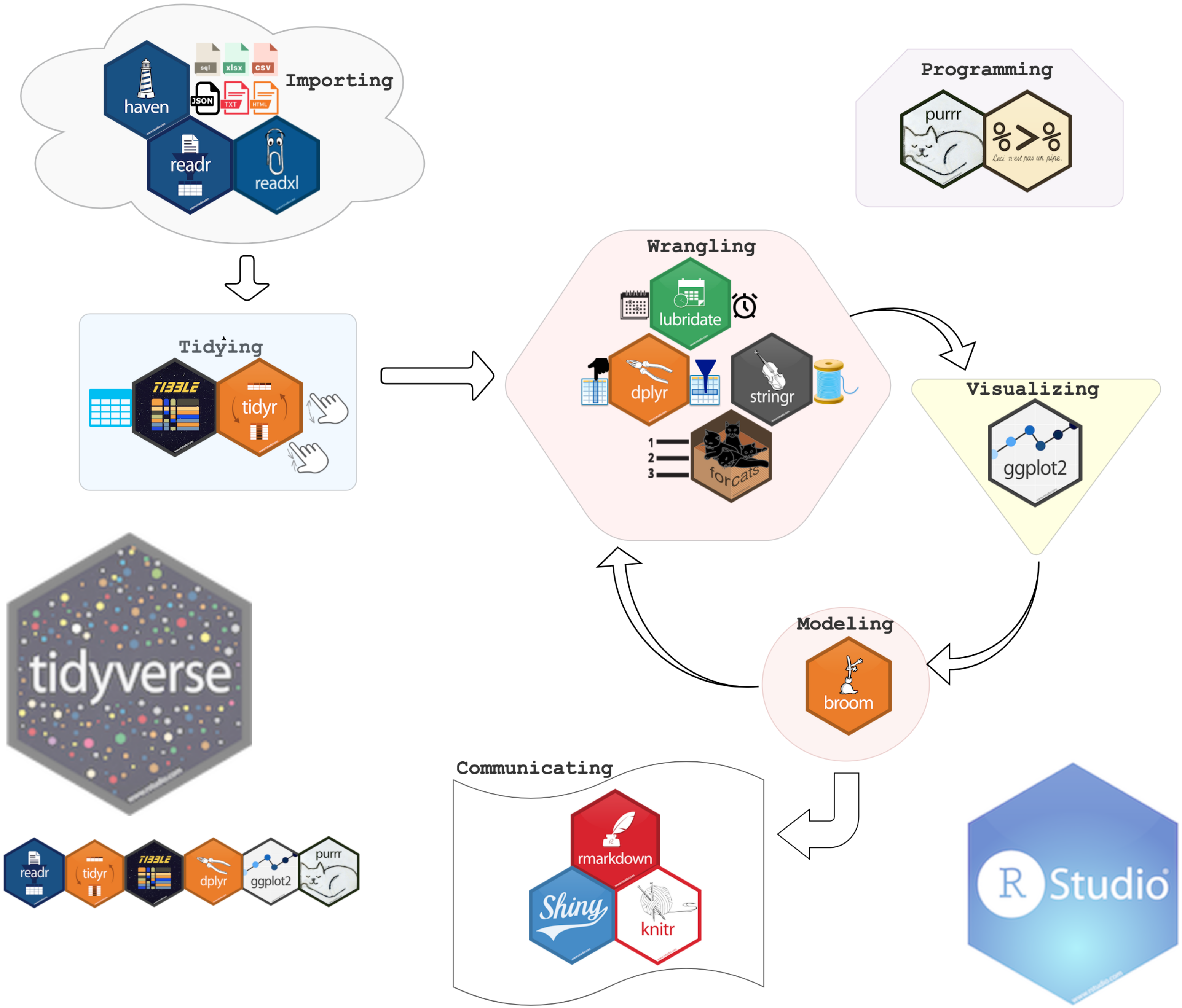
`require(tidyverse)` loads the 8 core packages:

- ggplot2
- readr
- stringr
- dplyr
- purrr
- forcats
- tidyr
- tibble

`install.package(tidyverse)` installs many other packages, including:

- lubridate
- readxl

Today you will use 5-6 packages from the tidyverse!


Importing
sql
xlsx
csv
JSON
TXT
HTML
haven
readr
readxl
Programming
purrr
%>%
Tidying
TIBBLE
tidyr
Wrangling
lubridate
dplyr
stringr
forcats
Visualizing
ggplot2
Modeling
broom
Communicating
rmarkdown
Shiny
knitr
tidyverse
readr
tidyr
TIBBLE
dplyr
ggplot2
purrr
R Studio

A tibble instead of a data.frame

Within the {tidyverse} tibbles are a modern take on data frames:

- keep the features that have stood the test of time
- drop the features that used to be convenient but are now frustrating.

You can use:

- `tibble()` to create a new tibble
- `as_tibble()` transforms an object (e.g. a data frame) into a tibble.

Inspect the differences:

```
str(mtcars, list.len = 5)
## 'data.frame':    32 obs. of  11 variables:
##  $ mpg : num  21 21 22.8 21.4 18.7 18.1 14.3 24.4 22
##  $ cyl : num  6 6 4 6 8 6 8 4 4 6 ...
##  $ disp: num  160 160 108 258 360 ...
##  $ hp  : num  110 110 93 110 175 105 245 62 95 123
##  $ drat: num  3.9 3.9 3.85 3.08 3.15 2.76 3.21 3.69
##   [list output truncated]

str(as_tibble(mtcars), list.len = 5)
## tibble [32 x 11] (S3: tbl_df/tbl/data.frame)
##  $ mpg : num [1:32] 21 21 22.8 21.4 18.7 18.1 14.3 2
##  $ cyl : num [1:32] 6 6 4 6 8 6 8 4 4 6 ...
##  $ disp: num [1:32] 160 160 108 258 360 ...
##  $ hp  : num [1:32] 110 110 93 110 175 105 245 62 95
##  $ drat: num [1:32] 3.9 3.9 3.85 3.08 3.15 2.76 3.21
##   [list output truncated]
```

Pipes in R

In R, the pipe operator is `%>%`.

It takes the output of one statement and makes it the input of the next statement.

When describing it, you can think of it as a "THEN".

A first example:

```r
diamonds %>% subset(cut == "Ideal")
```

is equivalent to:

```r
subset(diamonds, cut == "Ideal")
```

Data manipulation verbs

The `dplyr` package holds many useful data manipulation verbs:

- `mutate()` adds new variables that are functions of existing variables
- `select()` picks variables based on their names
- `filter()` picks cases based on their values
- `summarise()` reduces multiple values down to a single summary
- `arrange()` changes the ordering of the rows.

These all combine naturally with `group_by()` which allows you to perform any operation “by group”.

Use the `%>%` for multistep operations. This passes result on left into first argument of function on right.

filter()

Extract rows that meet logical criteria.

Here you go:

- inspect the `mtcars` data set
- filter observations with `hp` larger than 200

```
mtcars %>% filter(hp > 200)
##                      mpg cyl disp  hp drat    wt  qsec vs am gear carb
## Duster 360          14.3   8  360 245 3.21 3.570 15.84  0  0    3    4
## Cadillac Fleetwood  10.4   8  472 205 2.93 5.250 17.98  0  0    3    4
## Lincoln Continental 10.4   8  460 215 3.00 5.424 17.82  0  0    3    4
## Chrysler Imperial   14.7   8  440 230 3.23 5.345 17.42  0  0    3    4
## Camaro Z28          13.3   8  350 245 3.73 3.840 15.41  0  0    3    4
## Ford Pantera L      15.8   8  351 264 4.22 3.170 14.50  0  1    5    4
## Maserati Bora       15.0   8  301 335 3.54 3.570 14.60  0  1    5    8
```

filter() (cont.)

Here is an overview of logical tests:

`x < y`	Less than
`x > y`	Greater than
`x == y`	Equal to
`x <= y`	Less than or equal to
`x >= y`	Greater than or equal to
`x != y`	Not equal to
`x %in% y`	Group membership
`is.na(x)`	Is NA
`!is.na(x)`	Is not NA

mutate()

Create new columns.

Here you go:

- inspect the `mtcars` data set
- create a new variable `hp_per_wt`

```
mtcars %>% filter(hp > 200) %>% mutate(hp_per_wt = hp / wt)
##                      mpg cyl disp  hp drat    wt  qsec vs am gear carb
## Duster 360          14.3   8  360 245 3.21 3.570 15.84  0  0    3    4
## Cadillac Fleetwood  10.4   8  472 205 2.93 5.250 17.98  0  0    3    4
## Lincoln Continental 10.4   8  460 215 3.00 5.424 17.82  0  0    3    4
## Chrysler Imperial   14.7   8  440 230 3.23 5.345 17.42  0  0    3    4
## Camaro Z28          13.3   8  350 245 3.73 3.840 15.41  0  0    3    4
## Ford Pantera L      15.8   8  351 264 4.22 3.170 14.50  0  1    5    4
## Maserati Bora       15.0   8  301 335 3.54 3.570 14.60  0  1    5    8
##                     hp_per_wt
## Duster 360           68.62745
## Cadillac Fleetwood   39.04762
## Lincoln Continental  39.63864
## Chrysler Imperial    43.03087
## Camaro Z28           63.80208
```

summarise()

Compute table of summaries.

Here you go:

- inspect the `mtcars` data set
- calculate mean and standard deviation of `hp` and `wt`

```
mtcars %>% summarise(hp_mean = mean(hp),
                     hp_sd = sd(hp),
                     wt_mean = mean(wt),
                     wt_sd = sd(wt))
##    hp_mean    hp_sd wt_mean     wt_sd
## 1 146.6875 68.56287 3.21725 0.9784574
```

or in more compact notation with `across`:

```
mtcars %>% summarise(across(c(hp, wt),
                            list(mean2 = mean, sd2 = sd)))
##   hp_mean2   hp_sd2 wt_mean2    wt_sd2
## 1 146.6875 68.56287  3.21725 0.9784574
```

group_by()

Groups cases by common values of one or more columns.

Here you go:

- inspect the `mtcars` data set
- calculate mean of `hp` and `disp` by levels of `cyl`

```
mtcars %>% group_by(cyl) %>% summarise(hp_mean = mean(hp),
                                       disp_mean = mean(disp))
```

```
##   cyl   hp_mean disp_mean
## 1   4  82.63636  105.1364
## 2   6 122.28571  183.3143
## 3   8 209.21429  353.1000
```

Your turn

Discover some insights on claim frequency and severity in the MTPL portfolio.

Some options are listed below:

1. Calculate the overall empirical claim frequency in the portfolio as `sum(NCLAIMS) / sum(EXP)`. Now do the same, but with separate values for each gender (`SEX`) and/or type of fuel (`FUEL`).

2. Filter the observations with a claim and calculate the average claim severity as `weighted.mean(AVG, NCLAIMS)`. Do the same but for each type of coverage separately.

My solution for **Q1**:

```
mtpl_tidy %>%
  summarise(freq = sum(NCLAIMS) / sum(EXP)) %>%
  as.data.frame()
##        freq
## 1 0.1393352

mtpl_tidy %>% group_by(SEX) %>%
  summarise(freq = sum(NCLAIMS) / sum(EXP)) %>%
  as.data.frame()
##      SEX      freq
## 1   male 0.1361164
## 2 female 0.1484325

mtpl_tidy %>% group_by(SEX, FUEL) %>%
  summarise(freq = sum(NCLAIMS) / sum(EXP)) %>%
  as.data.frame()
##      SEX     FUEL      freq
## 1   male gasoline 0.1268247
## 2   male   diesel 0.1545461
## 3 female gasoline 0.1417593
## 4 female   diesel 0.1711736
```

My solution for **Q2**:

```
mtpl_tidy %>% filter(NCLAIMS > 0) %>%
  summarise(sev = weighted.mean(AVG, NCLAIMS)) %>%
  as.data.frame()
##        sev
## 1 1620.055

mtpl_tidy %>% filter(NCLAIMS > 0) %>%
  group_by(COVERAGE) %>%
  summarise(sev = weighted.mean(AVG, NCLAIMS)) %>%
  as.data.frame()
##   COVERAGE      sev
## 1      TPL 1722.811
## 2       PO 1276.656
## 3       FO 1833.615
```

More on data visualization in R

Basic plot instructions

Create a scatterplot with the `plot()` function:

```
plot(AGEPH ~ POWER, data = mtpl_tidy[1:1000, ],
     pch = 12, col = "blue", xlim = c(10, 150),
     main = 'Basic scatterplot')
```

Draw a function over the interval [from, to] with `curve()`:

```
curve(dnorm, from = -5, to = 5,
      col = "red", lwd = 3,
      main = "Standard normal density distribution")
```

Plots with ggplot2

The aim of the {ggplot2} package is to create elegant data visualisations using the grammar of graphics.

Here are the basic steps:

- begin a plot with the function `ggplot()` creating a coordinate system that you can add layers to
- the first argument of `ggplot()` is the dataset to use in the graph

Thus

```r
library(ggplot2)
ggplot(data = mtpl_tidy)
```

creates an empty graph.

Plots with ggplot2 (cont.)

You complete your graph by adding one or more **layers** to `ggplot()`.

For example:

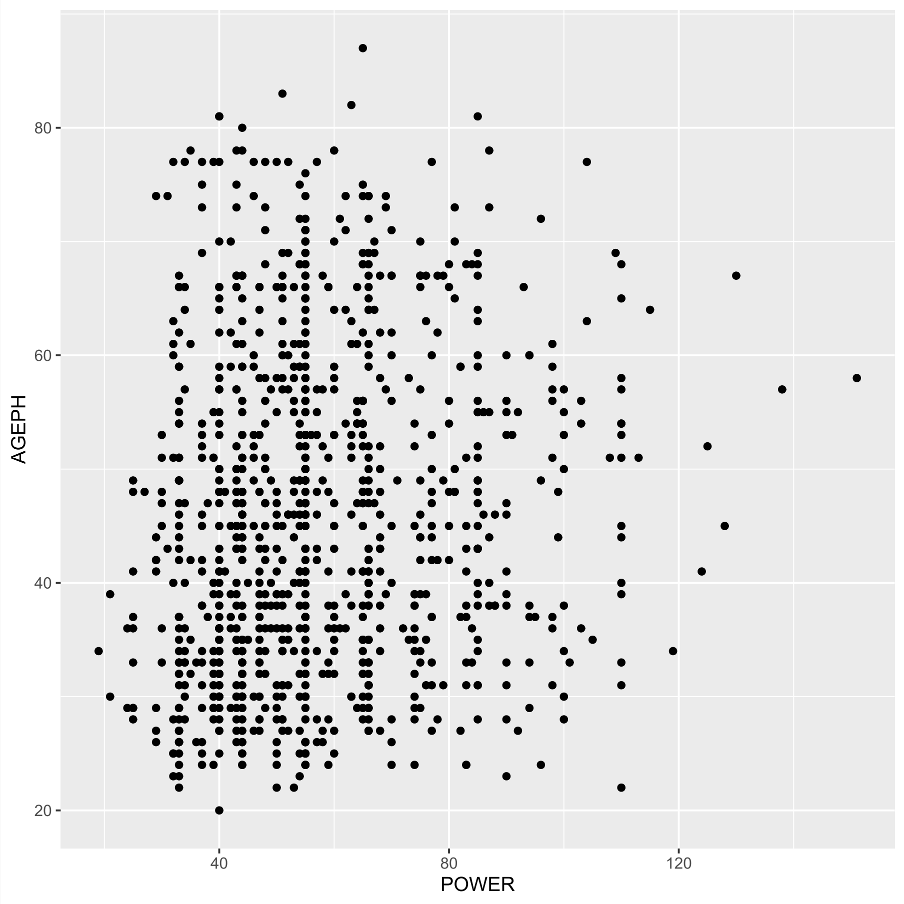
- `geom_point()` adds a layer of points to your plot, which creates a scatterplot
- `geom_smooth()` adds a smooth line
- `geom_bar` a bar plot.

Each geom function in `ggplot2` takes a **mapping** argument:

- how variables in your dataset are mapped to visual properties
- always paired with `aes()` and the x and y arguments of `aes()` specify which variables to map to the x and y axes.

Scatterplot with ggplot2

```
ggplot(data = mtpl_tidy[1:1000, ]) + geom_point(mapping = aes(x = POWER, y = AGEPH))
```



Scatterplot with ggplot2 (cont.)

Fixed color defined **outside** `aes()`:

```
ggplot(data = mtpl_tidy[1:1000, ]) +
geom_point(mapping = aes(x = POWER, y = AGEPH),
           color = "blue")
```

Color based on variable defined **inside** `aes()`:

```
ggplot(data = mtpl_tidy[1:1000, ]) +
geom_point(mapping = aes(x = POWER, y = AGEPH,
                         color = SEX))
```

Multiple layers in one plot

Mappings defined **locally** in the `geom_` elements:

```
ggplot(data = mtpl_tidy[1:1000, ]) +
  geom_point(mapping = aes(x = POWER, y = AGEPH)) +
  geom_smooth(mapping = aes(x = POWER, y = AGEPH))
```

Mapping defined **globally** in `ggplot()`:

```
ggplot(data = mtpl_tidy[1:1000, ],
       mapping = aes(x = POWER, y = AGEPH)) +
geom_point() + geom_smooth()
```

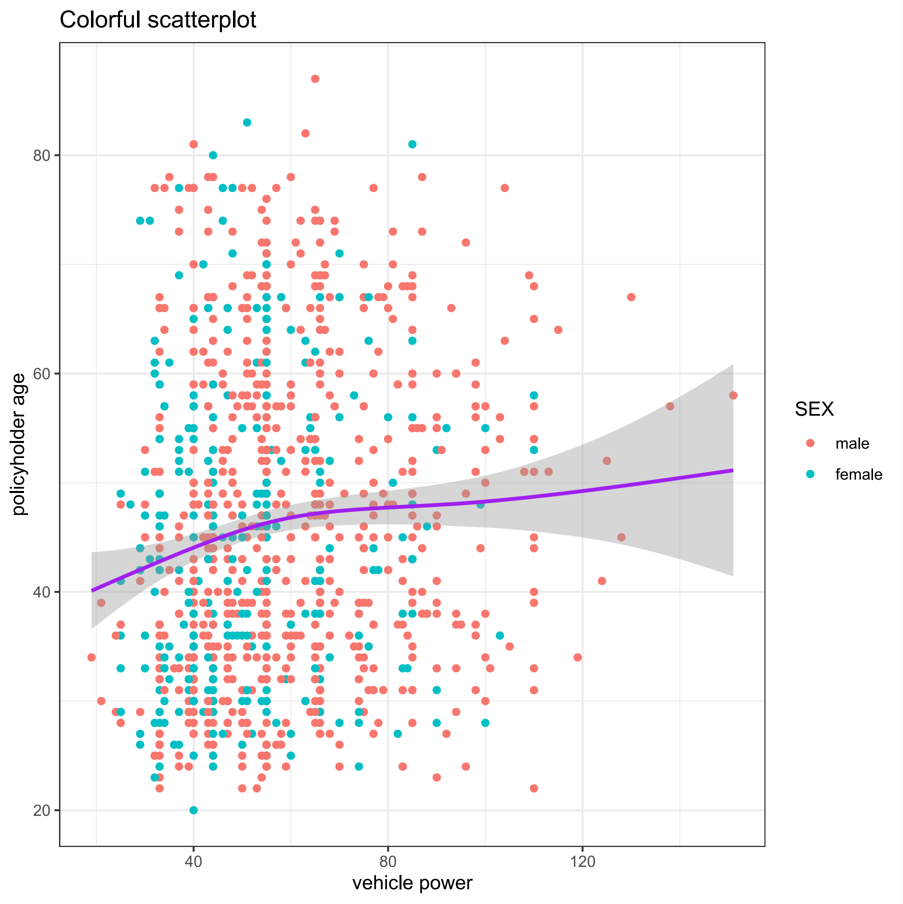
Customizing your ggplot

Global and local mappings can be combined together:

```
ggplot(data = mtpl_tidy[1:1000, ],
       mapping = aes(x = POWER, y = AGEPH)) +
  geom_point(aes(color = SEX)) +
  geom_smooth(color = 'purple') +
  labs(x = 'vehicle power',
       y = 'policyholder age') +
  ggtitle('Colorful scatterplot') +
  theme_bw()
```

- `labs` defines axis labels
- `ggtitle` defines a title
- `theme_bw` removes gray background

This is the result:



Your turn

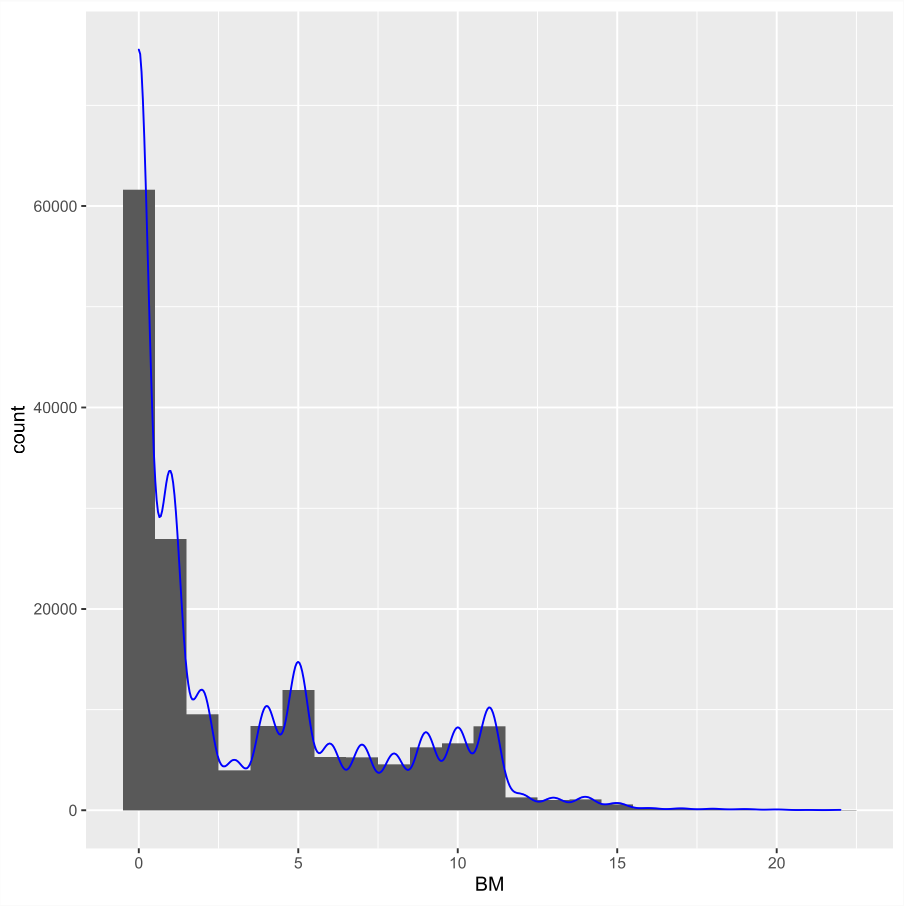
Play around with different `geom_` elements to discover the MTPL data.

Some options are listed below:

1. Draw a histogram for the bonus-malus level `BM` with `geom_histogram`. Try to overlay the histogram with a density via `geom_density`.
2. Create a barplot of `FUEL` with `geom_bar`. Try to split the distribution by `SEX` via the **fill** aesthetic.
3. Draw a boxplot of the vehicle age `AGEC`, split by the `USE` of the vehicle.
4. Create a 2D hexogram plot for `AGEPH` and `POWER` via `geom_hex`. Install {hexbin} first.

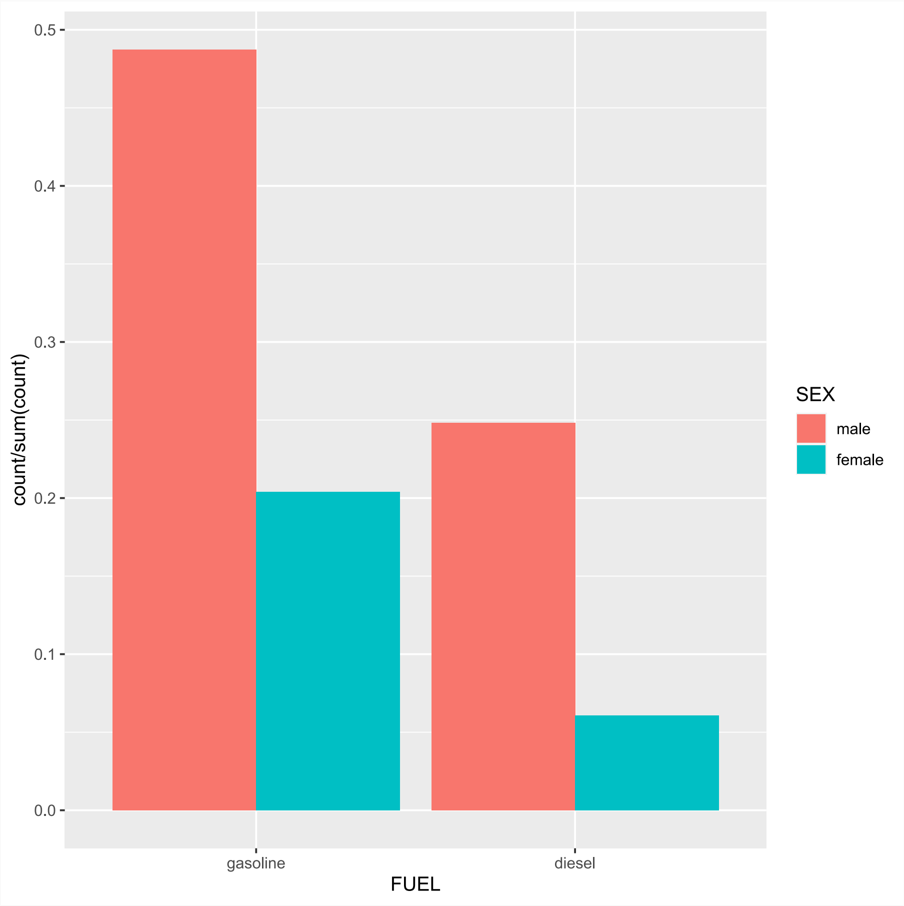
My solution for **Q1**:

```
ggplot(mtpl_tidy, aes(x = BM)) +
  geom_histogram(binwidth = 1) +
  geom_density(aes(y = ..count..), color = "blue")
```



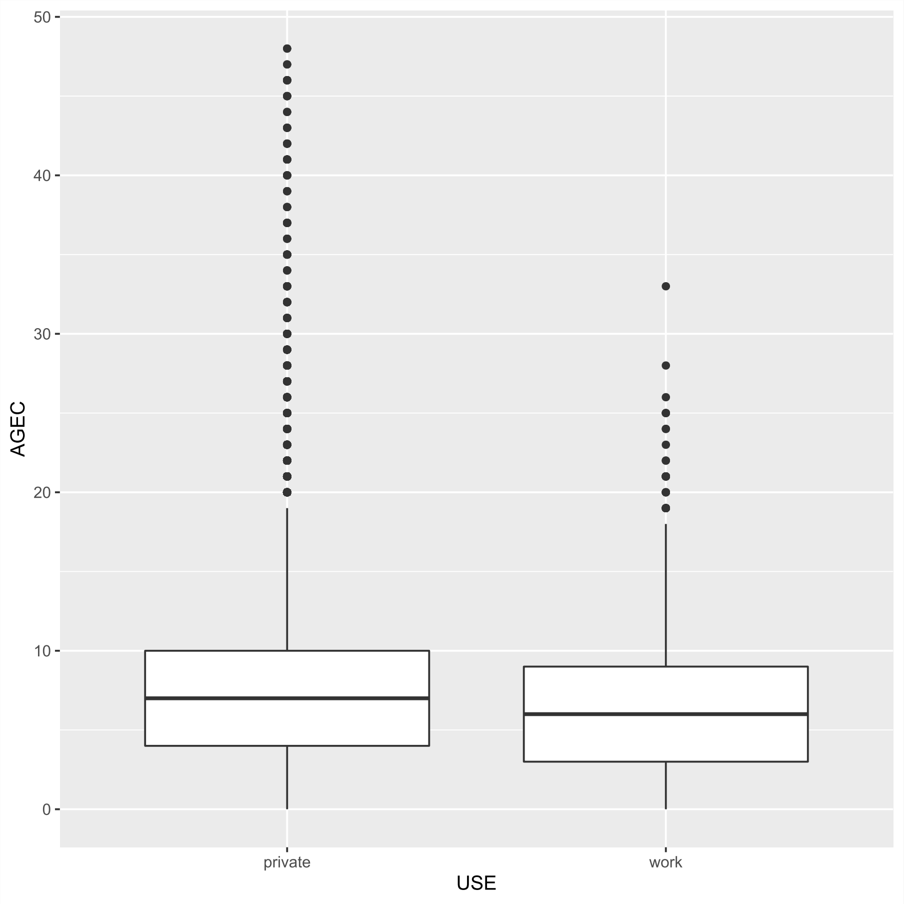
My solution for **Q2**:

```
ggplot(mtpl_tidy, aes(x = FUEL, fill = SEX)) +
  geom_bar(aes(y = ..count../sum(..count..)),
           position = 'dodge')
```



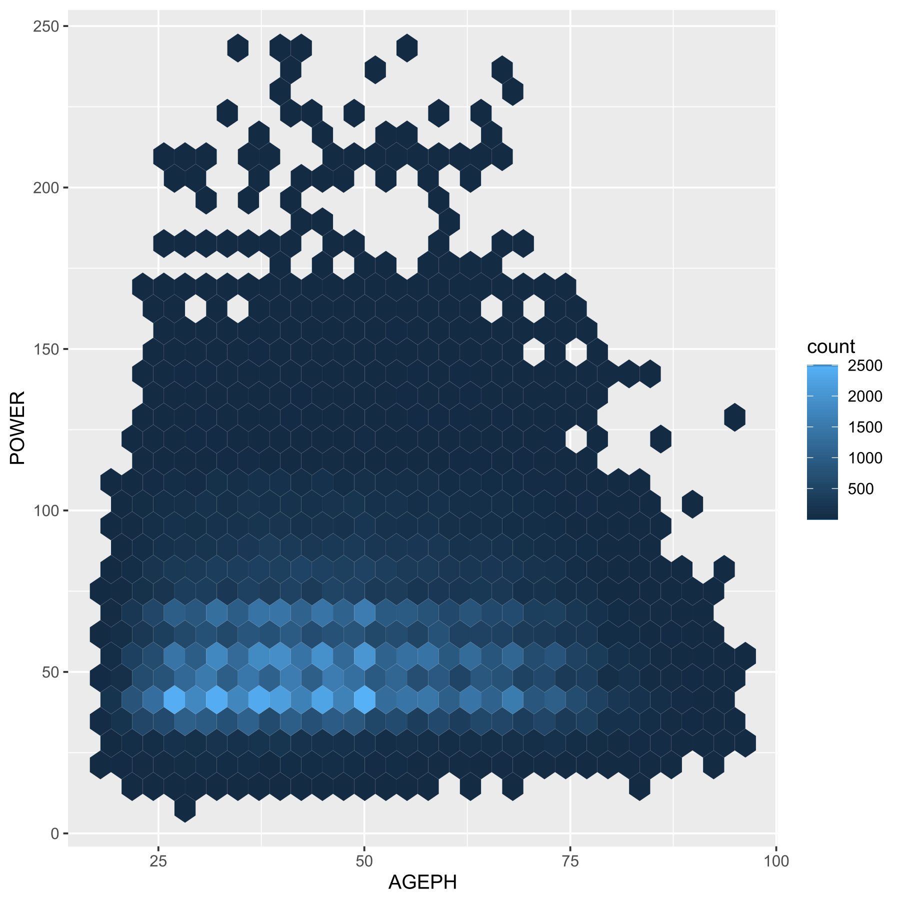
My solution for **Q3**:

```
ggplot(mtpl_tidy, aes(x = USE, y = AGEC)) +
  geom_boxplot()
```



My solution for **Q4**:

```
library(hexbin)
ggplot(mtpl_tidy, aes(x = AGEPH, y = POWER)) +
  geom_hex()
```



Conditionals and control flow

Relational operators

You'll first learn about relational operators to see how R objects compare.

```
3 == (2 + 1)
## [1] TRUE
"intermediate" == "r"
## [1] FALSE
(1 + 2) > 4
## [1] FALSE
katrien <- c(19, 22, 4, 5, 7)
katrien > 5
## [1]  TRUE  TRUE FALSE FALSE  TRUE
```

Make sure not to mix up `==` and `=`, where the latter is used for assignment and the former checks equality.

Logical operators

Logical operators are used to combine logicals.

The AND operator `&` needs all `TRUE` values to be `TRUE`:

```
TRUE & TRUE
## [1] TRUE
5 <= 5 & 2 > 3
## [1] FALSE
```

The OR operator `|` needs one `TRUE` value to be `TRUE`:

```
FALSE | TRUE
## [1] TRUE
3 < 3 | 7 < 6
## [1] FALSE
```

The NOT operator `!` reverses the result of a logical value:

```
! TRUE
## [1] FALSE
! 5 > 10
## [1] TRUE
```

These operators can be applied to vectors:

```
katrien <- c(19, 22, 4, 5, 7)
jan <- c(34, 55, 76, 25, 4)
katrien > 5 & jan <= 30
## [1] FALSE FALSE FALSE FALSE  TRUE
```

Conditionals

Time to check the `if` statement in R:

```
num_attendees ← 30

if (num_attendees > 5) {
  print("You're popular!")
}
[1] "You're popular!"
```

and the `if else`:

```
num_attendees ← 5

if (num_attendees > 5) {
  print("You're popular!")
} else {
  print("You are not so popular!")
}
[1] "You are not so popular!"
```

We can use `elseif()` arbitrarily many times following an `if()` statement:

```
x ← -2

if (x^2 < 1) {
  x^2
} else if (x ⩾ 1) {
  2*x-1
} else {
 -2*x-1
}
## [1] 3
```

For quick decision making use `ifelse()`

```
ifelse(x > 0, x, -x)
## [1] 2
```

Conditionals (cont.)

Instead of an `if()` statement followed by `elseif()` statements (and perhaps a final else), we can use `switch()`.

We pass a variable to select on, then a value for each option:

```
type_of_summary <- "mode"

switch(type_of_summary,
       mean = mean(x_vector),
       median = median(x_vector),
       histogram = hist(x_vector),
       "I don't understand")
## [1] "I don't understand"
```

Loops in R

A `for` loop runs for a fixed number of times:

```r
primes <- c(2, 3, 5, 7)

# loop version 1
for (p in primes) {
  print(p)
}
[1] 2
[1] 3
[1] 5
[1] 7

# loop version 2
for (i in 1:length(primes)) {
  print(primes[i])
}
[1] 2
[1] 3
[1] 5
[1] 7
```

A `while` loop runs until a condition is not met anymore:

```r
todo <- 64

while (todo > 30) {
  print("Work harder")
  todo <- todo - 7
  print(todo)
}
[1] "Work harder"
[1] 57
[1] "Work harder"
[1] 50
[1] "Work harder"
[1] 43
[1] "Work harder"
[1] 36
[1] "Work harder"
[1] 29
```

Your turn

1. Create a piece of code that prints the numbers from 2 up to 7, along with the message 'Divisible by 2 and 3', 'Divisible by 2 or 3' or 'Not divisible by 2 and 3'. Start from the structure below and fill in the gaps `...`.

2. Adjust the code created in 1. to work with `ifelse` instead.

```
for(num in ... ) {
  print(num)
  ... (num %% 2 == 0 ... num %% 3 == 0) {
    print('Divisible by 2 and 3')
  } ... (num %% 2 == 0 ... num %% 3 == 0) {
    print('Divisible by 2 or 3')
  } ... {
    print('Not divisible by 2 or 3')
  }
}
```

My solution for **Q1**:

```r
for(num in 2:7) {
  print(num)
  if (num %% 2 == 0 & num %% 3 == 0) {
    print('Divisible by 2 and 3')
  } else if (num %% 2 == 0 | num %% 3 == 0) {
    print('Divisible by 2 or 3')
  } else {
    print('Not divisible by 2 or 3')
  }
}
## [1] 2
## [1] "Divisible by 2 or 3"
## [1] 3
## [1] "Divisible by 2 or 3"
## [1] 4
## [1] "Divisible by 2 or 3"
## [1] 5
## [1] "Not divisible by 2 or 3"
## [1] 6
## [1] "Divisible by 2 and 3"
## [1] 7
## [1] "Not divisible by 2 or 3"
```

My solution for **Q2**:

```r
for(num in 2:7) {
  print(num)
  print(ifelse(num %% 2 == 0 & num %% 3 == 0,
               'Divisible by 2 and 3',
                ifelse(num %% 2 == 0 | num %% 3 == 0,
                       'Divisible by 2 or 3',
                       'Not divisible by 2 or 3')))
}
## [1] 2
## [1] "Divisible by 2 or 3"
## [1] 3
## [1] "Divisible by 2 or 3"
## [1] 4
## [1] "Divisible by 2 or 3"
## [1] 5
## [1] "Not divisible by 2 or 3"
## [1] 6
## [1] "Divisible by 2 and 3"
## [1] 7
## [1] "Not divisible by 2 or 3"
```

Writing functions

Write your own function

Creating a function in R is basically the assignment of a function object to a variable:

```
My_sqrt ← function(x) {
  sqrt(x)
}

# use the function
My_sqrt(12)
[1] 3.464102
```

With no explicit `return()` statement, the default is just to return whatever is on the last line.

You can define default argument values in your functions:

```
My_sqrt ← function(x, print_info = TRUE) {
  y ← sqrt(x)
  if (print_info) {
    print(paste("sqrt", x, "equals", y))
  }
  return(y)
}

# some calls of the function
My_sqrt(16)
[1] "sqrt 16 equals 4"
[1] 4
My_sqrt(16, FALSE)
[1] 4
My_sqrt(16, TRUE)
[1] "sqrt 16 equals 4"
[1] 4
```

Vectorized thinking

R works in a vectorized way.

Check this by calling the function `My_sqrt` on an input vector:

```
My_sqrt(c(16, 36, 64))
## [1] "sqrt 16 equals 4" "sqrt 36 equals 6" "sqrt 64 equals 8"
## [1] 4 6 8
My_sqrt(c(16, 36, 64), FALSE)
## [1] 4 6 8
```

What the function can see and do

Some things to keep in mind:

- each function has its own environment
- names here override names in the global environment
- internal environment starts with the named arguments
- assignments inside the function only change the internal environment
- names undefined in the function are looked for in the global environment.

Your turn

1. Create a function that will return the sum of 2 integers
2. Create a function that given a vector and an integer will return how many times the integer appears inside the vector.
3. Create a function that given a vector will print by default the mean and the standard deviation, it will optionally also print the median. Start from the structure below and fill in the gaps `...`.
4. Adjust the function created in 3. so that it returns a list with the mean, median and standard deviation.

```
My_mean_SD ← function(x, med = FALSE) {
  mean_x ← ...
  stdv_x ← ...
  cat("Mean is:", ... , ", SD is:", ... , "\n")

  if( ... ){
    median_x ← ...
    cat("Median is:", ... , "\n")
  }
}
```

My solution for **Q1**:

```r
My_sum <- function (x, y) {
  return(x + y)
}

My_sum(5, 10)
## [1] 15

My_sum(-1, -7)
## [1] -8

My_sum(1:3, 5:7)
## [1]  6  8 10
```

My solution for **Q2**:

```r
My_count <- function (v, x) {
  count <- 0
  for (i in 1:length(v)) {
    if (v[i] == x) {
      count <- count + 1
    }
  }
  return(count)
}

My_count(c(1,2,3,3,3,4,5,6,3,3), 3)
[1] 5

My_count(c(1:9, rep(10, 100), 11:35), 10)
[1] 100
```

My solution for **Q3**:

```r
My_mean_SD ← function(x, med = FALSE) {
  mean_x ← round(mean(x), 1)
  stdv_x ← round(sd(x), 1)
  cat("Mean is:", mean_x, ", SD is:", stdv_x, "\n")

  if(med){
    median_x ← median(x)
    cat("Median is:", median_x , "\n")
  }
}

My_mean_SD(rep(5, 3), med = FALSE)
Mean is: 5 , SD is: 0

My_mean_SD(1:10, med = TRUE)
Mean is: 5.5 , SD is: 3
Median is: 5.5
```

My solution for **Q4**:

```r
My_mean_SD ← function(x, med = FALSE) {
  if(!med) return(list(mean = round(mean(x), 1),
                       stdev = round(sd(x), 1)))
  return(list(mean = round(mean(x), 1),
              stdev = round(sd(x), 1),
              median = median(x)))
}

My_mean_SD(rep(5, 3), med = FALSE)
$mean
[1] 5

$stdev
[1] 0

My_mean_SD(1:10, med = TRUE)
$mean
[1] 5.5

$stdev
[1] 3

$median
[1] 5.5
```

Thanks!

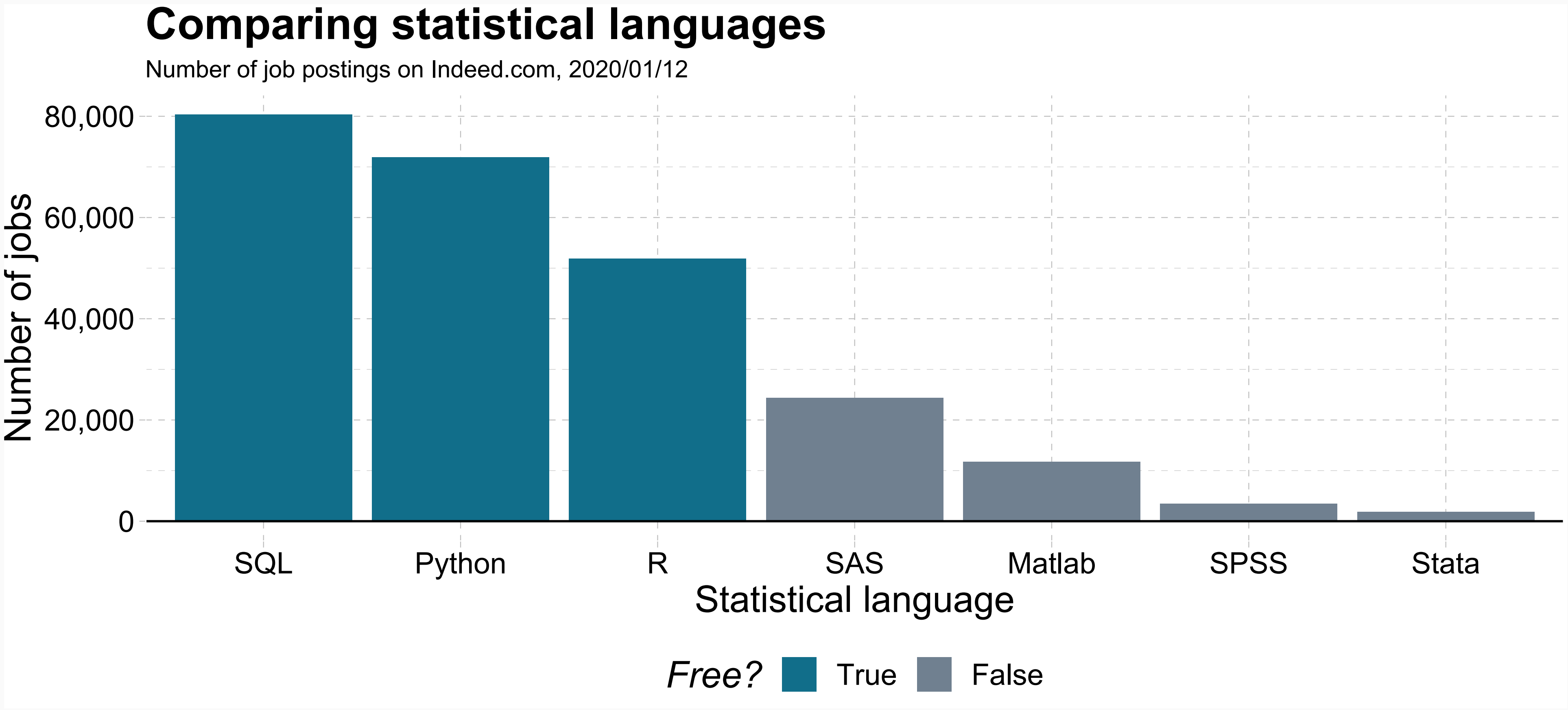
Slides created with the R package xaringan.

Course material available via

https://github.com/katrienantonio/werkt-U-al-met-R

Appendix: extra sheets

Why R and RStudio?



This graph is created from the search results obtained via www.indeed.com (on Jan 12, 2020), using Grant McDermott's code for `ggplot2`, see lecture 1 in his Data science for economists course.

Why R and RStudio? (cont.)

Data science positivism

- Next to Python, R has become the *de facto* language for data science, with a cutting edge *machine learning toolbox*.
- See: The Popularity of Data Science Software
- R is open-source with a very active community of users spanning academia and industry.

Bridge to actuarial science, econometrics and other tools

- R has all of the statistics and econometrics support, and is amazingly adaptable as a “glue” language to other programming languages and APIs.
- R does not try to be everything to everyone. The RStudio IDE and ecosystem allow for further, seemless integration (with e.g. python, keras, tensorflow or C).
- Widely used in actuarial undergraduate programs

Disclaimer + Read more

- It's also the language that we know best.
- If you want to read more: R-vs-Python, when to use Python or R or Hadley Wickham on the future of R

Join operations in dplyr

A **join** operation in database terminology is a merging of two data frames.

There are 4 types of joins:

- **Inner join** (or join): retain just the rows each table that match the condition
- **Left outer join** (or left join): retain all rows in the first table, and just the rows in the second table that match the condition
- **Right outer join** (or right join): retain just the rows in the first table that match the condition, and all rows in the second table
- **Full outer join** (or full join): retain all rows in both tables

Column values that cannot be filled in are assigned NA values

Join operations in dplyr (cont.)

We create a toy data set with policyholders[1]:

```
tab_1 <- data.frame(name = c("Alexis", "Bernie", "Charlie"),
                    children = 1:3,
                    stringsAsFactors = FALSE)
tab_2 <- data.frame(name = c("Alexis", "Bernie", "David"),
                    age = c(54, 34, 63),
                    stringsAsFactors = FALSE)
tab_1
##      name children
## 1  Alexis        1
## 2  Bernie        2
## 3 Charlie        3
tab_2
##     name age
## 1 Alexis  54
## 2 Bernie  34
## 3  David  63
```

[1] Courtesy of Ryan Tibshirani's course on Statistical computing.

inner_join()

We join `tab1` and `tab2` by name, but keep only customers in intersection:

```
tab_1
##      name children
## 1  Alexis        1
## 2  Bernie        2
## 3 Charlie        3
tab_2
##     name age
## 1 Alexis  54
## 2 Bernie  34
## 3  David  63

inner_join(x = tab_1, y = tab_2, by = "name")
##     name children age
## 1 Alexis        1  54
## 2 Bernie        2  34
```

left_join()

We join `tab_1` and `tab_2` by name, but keep all customers from `tab_1`:

```
tab_1
##      name children
## 1  Alexis        1
## 2  Bernie        2
## 3 Charlie        3
tab_2
##     name age
## 1 Alexis  54
## 2 Bernie  34
## 3  David  63

left_join(x = tab_1, y = tab_2, by = "name")
##      name children age
## 1  Alexis        1  54
## 2  Bernie        2  34
## 3 Charlie        3  NA
```

right_join()

We join `tab_1` and `tab_2` by name, but keep all customers from `tab_2`:

```
tab_1
##      name children
## 1  Alexis        1
## 2  Bernie        2
## 3 Charlie        3
tab_2
##     name age
## 1 Alexis  54
## 2 Bernie  34
## 3  David  63
```

```
right_join(x = tab_1, y = tab_2, by = "name")
##     name children age
## 1 Alexis        1  54
## 2 Bernie        2  34
## 3  David       NA  63
```

full_join()

Finally, suppose we want to join `tab_1` and `tab_2` by name, and keep all customers from both:

```
tab_1
##      name children
## 1  Alexis        1
## 2  Bernie        2
## 3 Charlie        3
tab_2
##     name age
## 1 Alexis  54
## 2 Bernie  34
## 3  David  63

full_join(x = tab_1, y = tab_2, by = "name")
##      name children age
## 1  Alexis        1  54
## 2  Bernie        2  34
## 3 Charlie        3  NA
## 4   David       NA  63
```