Introduction to R

Université Côte d'Azur - M2

Mattia Guerini

2020/2021 - fall semester

Introduction

Data structures

Basic Programming

Working with Data (`tydiverse` library)

Using Economic Data (`eurostat` library)

Plotting (`ggplot2` library)

Schedule

- 08th of October 10-12
- 15th of October 10-12
- 22nd of October 10-12
- 05th of November 10-12 (probably need to move this one)
- 12th of November 10-12
- 19th of November 10-12

Rules of the game

- arrive on time
- 5 min. break
- no book (plenty of open source resources on-line)
- slides https://github.com/mattiaguerini/intro_to_R
- take home exam (short project)

Introduction

What is R

R is both a programming language and software environment for statistical computing, which is free and open-source (https://www.r-project.org/about.html).

The *R Project* was initiated by Robert Gentleman and Ross Ihaka (University of Auckland) in the early 1990s as a different implementation of the S language, which was developed at Bell Laboratories.

Since 1997, R has been developed by the *R Development Core Team*.

R is platform independent and can run on Microsoft Windows, Mac OS and Unix/Linux systems.

Popularity: https://www.tiobe.com/tiobe-index/

Getting Started

To get started, you'll need to install two pieces of software:

- R, the actual programming language.
  https://cran.r-project.org
- RStudio, an excellent IDE for working with R.
  https://www.rstudio.com

Why RStudio?[1]

- Easier to use (everything is in one space)
- Many useful integrations (e.g. R-projects, R-markdown, shiny ...)
- Plenty of shortcuts (alt + shift + k)
- Plenty of cheatsheets (see top panel)

[1] You must have installed R before using RStudio.

Screenshot of RConsole

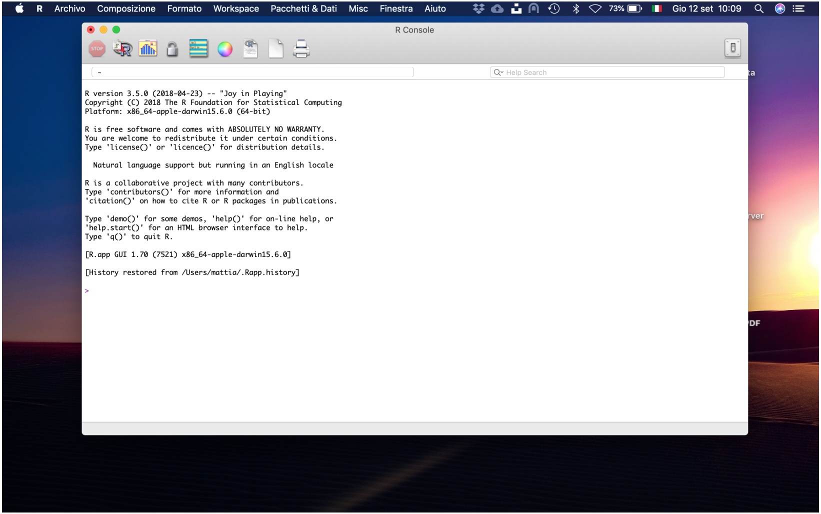


Figure 1: RConsole

Screenshot of RStudio

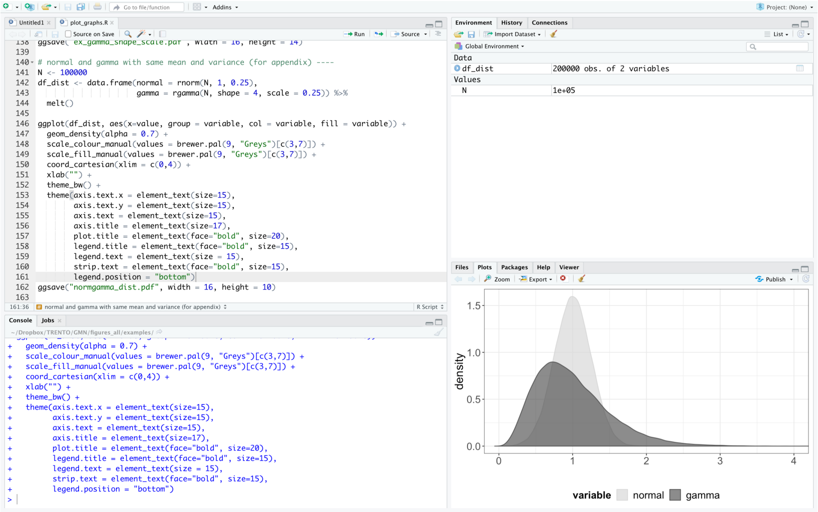


Figure 2: RStudio

Glossary

- *command*: user input (text or numbers) that R understands
- *script*: a sequence of commands collected in a text file, each separated by a new line
- *environment*: a list of named variables that we have generated/imported by means of a series of commands
- *history*: the list of past commands thaty we have used
- *help*: a documentation of all the functions available in R (the user manual)
- *package*: a collection of additional functions and dataset

R as a calculator (I)

```r
2+2
```

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

```r
2-2
```

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

```r
2*2
```

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

```r
2/2
```

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

R as a calculator (II)

```r
log(1)
```

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

```r
exp(1)
```

```
## [1] 2.718282
```

```r
log(exp(1))
```

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

```r
sqrt(25)
```

```
## [1] 5
```

The help

```
?log
help(log)
```

Otherwise:

- Google your error message
- Ask for help in Stack Overflow

Packages

R comes with a number of built-in functions and datasets, but one of the main strengths of R as an open-source project is its package system.

Packages gives you access to additional functions and datasets.

If you want to do something which is not doable with the R basic functions, there is a good chance that there exist a package that will fulfill your needs.

You can install packages using the command `install.packages()`

You can load packages using the command `library()`

Data structures

Data types

- Numeric/Double (e.g. 2.5, 1/5, 1.0, . . .)
- Integer (e.g. 1, 2, 3, . . .)
- Complex (e.g. 1 + 2i, . . .)
- Logical (e.g. TRUE, FALSE or NA)
- Character (e.g. “a”, “paper”, “2 plus 2 = 5”, “TRUE”, . . .)
- Factor/Categorical (“male”, “female”, . . .)

Data structures

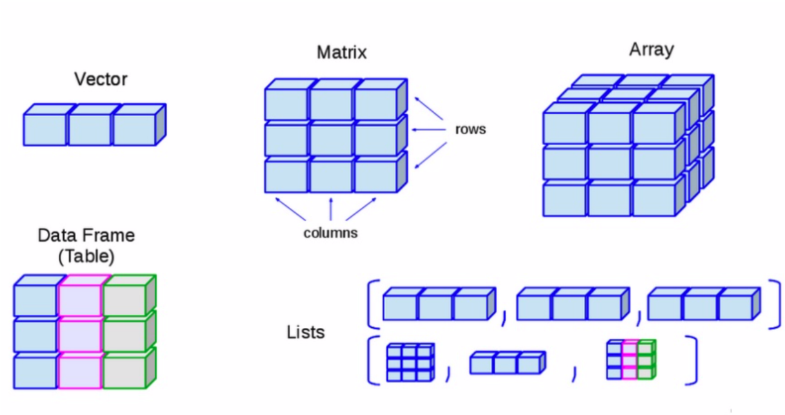


Figure 3: Visualization of data structures

Vectors (I)

You can create a vector using the command `c()`

```
x <- c(1, 3, 5, 10)
x
```

```
## [1]  1  3  5 10
```

Vectors must contain elements of the same data type.

```
c(1, "intro", TRUE)
```

```
## [1] "1"     "intro" "TRUE"
```

You can measure the length of a vector using the command `length()`

```
length(x)
```

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

Vectors (II)

It is also possible to easily create sequences

```r
1:10
```

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

```r
seq(from = 1, to = 2, by = 0.1)
```

```
##  [1] 1.0 1.1 1.2 1.3 1.4 1.5 1.6 1.7 1.8 1.9 2.0
```

```r
rep("A", times = 5)
```

```
## [1] "A" "A" "A" "A" "A"
```

Vectors (III)

You can combine different vectors

```
x <- 1:3 # from 1 to 3
y <- c(10, 15) # 10 and 15
z <- c(x,y) # x first and then y
z
```

```
## [1]  1  2  3 10 15
```

And you can repeat vectors (or its elements)

```
z <- rep(y, each=3) # repeat each element 3 times
z
```

```
## [1] 10 10 10 15 15 15
```

```
z <- rep(y, times=3) # repeat the whole vector 3 times
z
```

```
## [1] 10 15 10 15 10 15
```

Subsetting Vectors

```r
x <- c(1,5,10,7)
x < 6 # is the element lower than 6?
```

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

```r
x == 10 # is the element equal to 10?
```

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

```r
x[2] # which element is in the second position?
```

```
## [1] 5
```

```r
x[1:2] # which elements are in the first 2 positions?
```

```
## [1] 1 5
```

```r
x[c(1,3,4)] # which elements are in positions 1, 3 and 4?
```

```
## [1]  1 10  7
```

Vectors' Operations

```
x <- c(1,5,10,7)
x+2 # adds a scalar to all elements
```

```
## [1]  3  7 12  9
```

```
x^2 # what's the square of all elements?
```

```
## [1]   1  25 100  49
```

Matrices (I)

You can create a matrix using the command `matrix()`

```
X <- matrix(1:9, nrow = 3, ncol = 3)
X
```

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

Matrices (II)

R automatically inserts elements by columns, but we can ask to include by rows

```
X <- matrix(1:9, nrow = 3, ncol = 3, byrow = TRUE)
X
```

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

You don't even have to specify the options names

```
X <- matrix(1:8, 2, 4, T)
X
```

```
##      [,1] [,2] [,3] [,4]
## [1,]    1    2    3    4
## [2,]    5    6    7    8
```

Matrices (III)

Matrices can also be created by combining vectors

```
X <- cbind(1:4, 6:9) # binds them as columns
X
```

```
##      [,1] [,2]
## [1,]    1    6
## [2,]    2    7
## [3,]    3    8
## [4,]    4    9
```

```
X <- rbind(1:4, 6:9) # binds them as rows
X
```

```
##      [,1] [,2] [,3] [,4]
## [1,]    1    2    3    4
## [2,]    6    7    8    9
```

Subsetting Matrices

```r
X>5 # elements larger than 5
```

```
##       [,1]  [,2]  [,3]  [,4]
## [1,] FALSE FALSE FALSE FALSE
## [2,]  TRUE  TRUE  TRUE  TRUE
```

```r
X[1,4] # element of first row, fourth column?
```

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

```r
X[1,] # element in the first row?
```

```
## [1] 1 2 3 4
```

```r
X[,2] # elements in the second columns?
```

```
## [1] 2 7
```

Matrices' Operations (I)

Let's create two matrices `X` and `Y`:

```
x <- c(1,5,4,9)
y <- c(2,4,1,3)
X <- matrix(x, 2, 2)
Y <- matrix(y, 2, 2)
X
```

```
##      [,1] [,2]
## [1,]    1    4
## [2,]    5    9
```

```
Y
```

```
##      [,1] [,2]
## [1,]    2    1
## [2,]    4    3
```

Matrices' Operations (II)

```
X+Y   # element by element (also subtraction is equal)
```

```
##      [,1] [,2]
## [1,]    3    5
## [2,]    9   12
```

```
X*Y   # element by element multiplication
```

```
##      [,1] [,2]
## [1,]    2    4
## [2,]   20   27
```

```
X%*%Y # matrix multiplication
```

```
##      [,1] [,2]
## [1,]   18   13
## [2,]   46   32
```

Matrices' Operations (III)

```r
solve(Y) # inverse
```

```
##      [,1] [,2]
## [1,]  1.5 -0.5
## [2,] -2.0  1.0
```

```r
t(X) # transpose
```

```
##      [,1] [,2]
## [1,]    1    5
## [2,]    4    9
```

Arrays (I)

```r
x <- 1:4
X <- array(data = x, dim = c(2,3,2))
X
```

```
## , , 1
##
##      [,1] [,2] [,3]
## [1,]    1    3    1
## [2,]    2    4    2
##
## , , 2
##
##      [,1] [,2] [,3]
## [1,]    3    1    3
## [2,]    4    2    4
```

Notes about the Arrays

- Remember that vectors, matrices and arrays can include only data types of the same kind.
- A 3D array is basically a combination of matrices each laid on top of other (e.g. write N KxK matrices in N different pages in your notebook)
- A 4D array is basically a combination of arrays each laid on top of other (e.g. take two notebooks of 3D arrays)
- A 5D array ...
- Pay attention to the `recycling rule` (https://cran.r-project.org/doc/manuals/r-devel/R-intro.html#The-recycling-rule)

Lists

A list is a one-dimensional heterogeneous data structure.

It is indexed like a vector with a single integer value (or a name), but each element can contain an element of any data type.

```
x <- 1:4
y <- c("a", "b", "c")
L <- list(numbers = x, letters = y)
L
```

```
## $numbers
## [1] 1 2 3 4
##
## $letters
## [1] "a" "b" "c"
```

Subsetting Lists

```
L[[1]] # extract the first element
```

```
## [1] 1 2 3 4
```

```
L$numbers # extract the element called numbers
```

```
## [1] 1 2 3 4
```

```
L$letters # extract the element called letters
```

```
## [1] "a" "b" "c"
```

You can even “work” with the subsetted element:

```
L$numbers[1:3] > 2
```

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

Data Frames (I)

A `data.frame` is similar to a typical `spreadsheet` in excel.

There are rows, and there are columns.

A row is typically thought of as an *observation*.

A column is a certain *variable*, characteristic or feature of that observation.

Data Frames (II)

A data frame is a list of column vectors where:

- each column has a name
- each column must contain the same data type, but the different columns can store different data types.
- each column must be of same length

Data Frames (III)

```
set.seed(1)
df <-  data.frame(id = 1:5,
  name = c("Diego", "Samuel", "Marco", "Javier", "Leonardo"),
  surname = c("Milito", "Eto'o", "Materazzi", "Zanetti", "Bonucci"),
  wage = rnorm(n=5, mean = 10^5, sd = 10^3), # normal random sample
  origin = c("Argentina", "Cameroon", "Italy", "Argentina", "Italy"),
  treble_winner = c(T, T, T, T, F)
  )
df
```

```
##   id     name   surname      wage    origin treble_winner
## 1  1    Diego    Milito  99373.55 Argentina          TRUE
## 2  2   Samuel     Eto'o 100183.64  Cameroon          TRUE
## 3  3    Marco Materazzi  99164.37     Italy          TRUE
## 4  4   Javier   Zanetti 101595.28 Argentina          TRUE
## 5  5 Leonardo   Bonucci 100329.51     Italy         FALSE
```

You can verify the size of the `data.frame` using the command `dim()`

You can get the `data type` info using the command `str()`

Subsetting Data Frames (I)

```
df$name # subset a column
```

```
## [1] Diego    Samuel   Marco    Javier   Leonardo
## Levels: Diego Javier Leonardo Marco Samuel
```

```
df[,c(2,5)] # can also subset like a matrix
```

```
##       name    origin
## 1    Diego Argentina
## 2   Samuel  Cameroon
## 3    Marco     Italy
## 4   Javier Argentina
## 5 Leonardo     Italy
```

Subsetting Data Frames (II)

```r
head(df, n=3) # first n observations
```

```
##   id   name   surname      wage    origin treble_winner
## 1  1  Diego    Milito  99373.55 Argentina          TRUE
## 2  2 Samuel     Eto'o 100183.64  Cameroon          TRUE
## 3  3  Marco Materazzi  99164.37     Italy          TRUE
```

```r
tail(df, n=3) # last n observations
```

```
##   id     name   surname      wage    origin treble_winner
## 3  3    Marco Materazzi  99164.37     Italy          TRUE
## 4  4   Javier   Zanetti 101595.28 Argentina          TRUE
## 5  5 Leonardo   Bonucci 100329.51     Italy         FALSE
```

Inspecting data frames (I)

R comes with many data bases included. These can be used for learning R.

One of the most famous is the one called `mtcars`.

```
head(mtcars)
```

```
##                    mpg cyl disp  hp drat    wt  qsec vs am gear carb
## Mazda RX4         21.0   6  160 110 3.90 2.620 16.46  0  1    4    4
## Mazda RX4 Wag     21.0   6  160 110 3.90 2.875 17.02  0  1    4    4
## Datsun 710        22.8   4  108  93 3.85 2.320 18.61  1  1    4    1
## Hornet 4 Drive    21.4   6  258 110 3.08 3.215 19.44  1  0    3    1
## Hornet Sportabout 18.7   8  360 175 3.15 3.440 17.02  0  0    3    2
## Valiant           18.1   6  225 105 2.76 3.460 20.22  1  0    3    1
```

```
dim(mtcars)
```

```
## [1] 32 11
```

Inspecting data frames (II)

```r
str(mtcars)
```

```
## 'data.frame':	32 obs. of  11 variables:
##  $ mpg : num  21 21 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 ...
##  $ 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 3.92 3.92 ...
##  $ wt  : num  2.62 2.88 2.32 3.21 3.44 ...
##  $ qsec: num  16.5 17 18.6 19.4 17 ...
##  $ vs  : num  0 0 1 1 0 1 0 1 1 1 ...
##  $ am  : num  1 1 1 0 0 0 0 0 0 0 ...
##  $ gear: num  4 4 4 3 3 3 3 4 4 4 ...
##  $ carb: num  4 4 1 1 2 1 4 2 2 4 ...
```

```r
names(mtcars)
```

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

Subsetting data frames (III)

We are interesting in the cylinders and the weights of inefficient cars (lower than 15 miles per gallon).

```
poll_cars <- mtcars[mtcars$mpg<15, c("cyl", "wt")]
poll_cars
```

```
##                     cyl    wt
## Duster 360            8 3.570
## Cadillac Fleetwood    8 5.250
## Lincoln Continental   8 5.424
## Chrysler Imperial     8 5.345
## Camaro Z28            8 3.840
```

Subsetting data frames (IV)

Alternatively:

```
poll_cars <- subset(mtcars, subset = mpg<15, select = c("cyl", "wt"))
poll_cars
```

```
##                     cyl    wt
## Duster 360            8 3.570
## Cadillac Fleetwood    8 5.250
## Lincoln Continental   8 5.424
## Chrysler Imperial     8 5.345
## Camaro Z28            8 3.840
```

Importing downloaded data frames

You can import csv data that you have downloaded from any external source using:

```
setwd("~/Google Drive/T_2020a_UCA_introR/data/")
nyc_ab <- read.csv("AB_NYC_2019.csv")
```

where:

- `setwd()` sets the working directory to the place where the data is saved;
- `read.csv()` loads the csv file with the specified name.

You can similarly import almost any kind of data file stored in other formats (.xls, .txt, .csv, .dta, .Rdata, .mat, ...)

Basic Programming

Variables

In programming, a variable denotes an object (i.e. a variable is a name or a label for something).

```
x <- 1
f <- function(x){x*2+2}
```

Notice that the argument x of the function is different from the x previously defined. The second is only local to the function and always required to be specified.

Try to compute 4 or 20.

Control Flows (I)

Also known as an if/else statement. It relates to ways in which you can adapt your code to different circumstances.

Based on a condition being TRUE, your program will do one thing, as opposed to another thing.

In R, the if/else syntax has the following structure:

```
if (condition == TRUE) {
  do_something
} else {
  do_something_different
}
```

```
## [1] "do something"
```

Control Flows (II) - Example

```r
x <- 1
y <- 3
if (x>y) {
  print("x is larger than y")
  z <- x*y
  print(paste0("z is equal to ", z))
} else {
  print("x is smaller or equal than y")
  z <- x*y - 1
  print(paste0("z is equal to ", z))
}
```

```
## [1] "x is smaller or equal than y"
## [1] "z is equal to 2"
```

Control Flows (III) - Example with more conditions

```r
x <- 3
y <- 3
if (x>y) {
  print("x is larger than y")
  z <- x*y + 1
  print(paste0("z is equal to ", z))
} else if (x==y) {
  print("x is equal than y")
  z <- x*y
  print(paste0("z is equal to ", z))
} else {
  print("x is smaller than y")
  z <- x*y - 1
  print(paste0("z is equal to ", z))
}
```

```
## [1] "x is equal than y"
## [1] "z is equal to 9"
```

Loops (I)

As the name suggests, in a loop the program repeats a set of instructions many times, until some condition tells it to stop.

A very powerful, yet simple, construction is that the program can count how many steps it has done already - which may be important to know for many algorithms.

The syntax of a `for` loop is the following:

```
for (i in 1:10){
  # does not have to be 1:10!
  # loop body: gets executed each time
  # the value of i changes with each iteration
}
```

Loops (II) - Example

Produce a loop that displays the double of the loop round.

```r
for (i in 1:5){
  y <- i*2
  print(y)
}
```

```
## [1] 2
## [1] 4
## [1] 6
## [1] 8
## [1] 10
```

Loops (III) - Example with more loops

You can even have loops into other loops.

These can be useful for exploring combinations of events:

```
quantity <- c(2,3)
fruits <- c("mangos", "apples", "bananas")

for (i in quantity){ # first nest: for each i
  for (j in fruits){ # second nest: for each j
    print(paste("Can I get",i,j,"please?"))
    }
}
```

```
## [1] "Can I get 2 mangos please?"
## [1] "Can I get 2 apples please?"
## [1] "Can I get 2 bananas please?"
## [1] "Can I get 3 mangos please?"
## [1] "Can I get 3 apples please?"
## [1] "Can I get 3 bananas please?"
```

Functions (I)

So far we have been using functions, but haven't actually discussed some of their details.

A function is a set of instructions that R executes for us, much like those collected in a script file.

The good thing is that functions are much more flexible than scripts, since they can depend on input arguments, which change the way the function behaves.

Functions (II)

Here is how to define a function in general:

```
function_name <- function(arg1 ,arg2=default_value){
  # function body
  # you do stuff with arg1 and arg2
  # you can have any number of arguments, with or without defaults
  # any valid `R` commands can be included here
  # the last line is returned
}
```

Function (III) - Example

```r
hello <- function(your_name = "Lord Vader"){
  paste("You R most welcome,", your_name)
  # we could also write:
  # return(paste("You R most welcome,",your_name))
}
# we call the function by typing it's name with round brackets
```

```r
hello()
```

```
## [1] "You R most welcome, Lord Vader"
```

```r
hello("Mattia")
```

```
## [1] "You R most welcome, Mattia"
```

Exercise

We want to build a function called **`prices_info`** that perform the following operations for a series of asset prices:

- create a vector called **`average`** by computing the mean for each series
- create a vector called **`volatility`** by computing the standard deviation for each series
- create a vector called **`mu_large`** which is `TRUE` if $\mu >= 0$ and `FALSE` $\mu < 0$
- create a vector called **`sd_large`** which is `TRUE` if $\sigma >= 1$ and `FALSE` $\sigma < 1$ below 0
- create a vector called **`both_large`** which is `TRUE` only if $\mu >= 0$ and $\sigma >= 1$
- return these five vectors in a list

The asset prices are all random normals numbers and can be generated as follows:

```
set.seed(0)
asset_prices <- matrix(data = rnorm(1000), nrow = 10, byrow = T)
```

Working with Data (`tydiverse` library)

Tidyverse

The tidyverse is a collection of R packages designed for data science.

All packages share an underlying design philosophy, grammar, and data structures.

Useful info here: https://www.tidyverse.org

Install it with the command `install.packages("tidyverse")`

Load it with the command `library(tidyverse)`

Tidyverse packages (some of them)

The core `tidyverse` package includes (among the others)

- `magrittr` operators and verbs to decrease development time and improve readability of code (i.e. *to make your code smokin'*)
- `dplyr` set of verbs that solve the most common data manipulation challenges
- `tidyr` set of functions that help you get to tidy data.
- `readr` and `readxl` fast and friendly way to read rectangular data (like .csv and .xls)
- `ggplot2` system for declaratively creating graphics, based on The *Grammar of Graphics* (next section)

Note: it does not contain the 'reshape2' package!

from magrittr: the pipe operator

We'll learn the new commands using the `mtcars` dataset.

The operator `%>%` (Cmd + Shift + M) pipes the left-hand side values forward into expressions that appear on the right-hand side – e.g. one can replace f(x) with x %>% f().

```
9 %>%
  sqrt() %>%  # 3
  + 22        # 25
```

```
## [1] 25
```

```
mtcars %>%
  subset(mpg<15)
```

```
##                      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
```

from dplyr: `select()` variables by columns

Rather than using the `$` you can use select

```
?dplyr::select
```

```
head(select(mtcars, c(mpg, cyl)))
```

```
##                    mpg cyl
## Mazda RX4         21.0   6
## Mazda RX4 Wag     21.0   6
## Datsun 710        22.8   4
## Hornet 4 Drive    21.4   6
## Hornet Sportabout 18.7   8
## Valiant           18.1   6
```

from dplyr: `filter()` variables by row conditions

Rather than using the `subset` function you can use `filter`

```
?dplyr::filter
```

```
filter(mtcars, mpg<15)
```

```
##                      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
```

But. . . we lose the names of the cars!!

combining dplyr and magrittr

We can combine into a easily readable format functions from the two packages.

```
mtcars %>%
  rownames_to_column('name') %>% # from library tibble
  select(name, mpg, cyl) %>%
  filter(mpg<15)
```

```
##                  name  mpg cyl
## 1          Duster 360 14.3   8
## 2  Cadillac Fleetwood 10.4   8
## 3 Lincoln Continental 10.4   8
## 4   Chrysler Imperial 14.7   8
## 5          Camaro Z28 13.3   8
```

from dplyr: `mutate()` variables

What if we would like to measure consumption in km/l rather than m/g or if we need to measure the `log` of horsepowers.

```
mtcars %>%
  rownames_to_column('name') %>%
  select(name, mpg, hp) %>%
  filter(mpg<15) %>%
  mutate(kml = mpg*0.425144) %>% # 0.425144 is the conversion ratio
  mutate(lhp = log(hp))
```

```
##                  name  mpg  hp      kml      lhp
## 1          Duster 360 14.3 245 6.079559 5.501258
## 2  Cadillac Fleetwood 10.4 205 4.421498 5.323010
## 3 Lincoln Continental 10.4 215 4.421498 5.370638
## 4   Chrysler Imperial 14.7 230 6.249617 5.438079
## 5          Camaro Z28 13.3 245 5.654415 5.501258
```

from dplyr: arrange() variables

What if we don't like the order of the variables?

And what if we'd like to display them from most to least efficient (in terms of km/l)

```
mtcars %>%
  rownames_to_column('name') %>%
  select(name, mpg, hp) %>%
  filter(mpg<15) %>%
  mutate(kml = mpg*0.425144) %>% # 0.425144 is the conversion ratio
  mutate(lhp = log(hp)) %>%
  select(name, mpg, kml, hp, lhp) %>%
  arrange(desc(kml))
```

```
##                  name  mpg      kml  hp      lhp
## 1   Chrysler Imperial 14.7 6.249617 230 5.438079
## 2          Duster 360 14.3 6.079559 245 5.501258
## 3          Camaro Z28 13.3 5.654415 245 5.501258
## 4  Cadillac Fleetwood 10.4 4.421498 205 5.323010
## 5 Lincoln Continental 10.4 4.421498 215 5.370638
```

Digression on data frame formats

https://github.com/rstudio/cheatsheets/blob/master/data-import.pdf

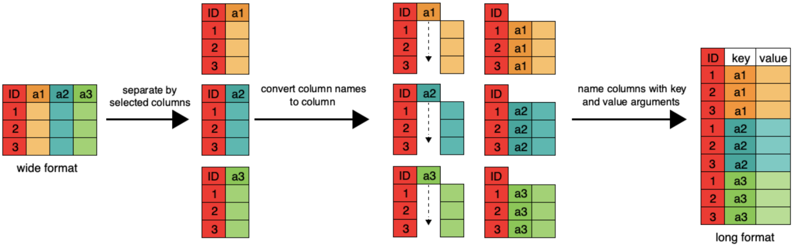


Figure 4: Data wrangle

Update (new names) https://tidyr.tidyverse.org/articles/pivot.html

from tidyr: pivot_longer() data frames

```
long_data <- mtcars %>%
  rownames_to_column('name') %>%
  select(name, mpg, hp) %>%
  filter(mpg<15) %>%
  mutate(kml = mpg*0.425144) %>% # 0.425144 is the conversion ratio
  select(name, mpg, kml) %>%
  pivot_longer(cols = c("mpg", "kml"),
               names_to = "variable",
               values_to = "value") %>%
  arrange(variable)
long_data
```

```
## # A tibble: 10 x 3
##    name                variable value
##    <chr>               <chr>    <dbl>
##  1 Duster 360          kml       6.08
##  2 Cadillac Fleetwood  kml       4.42
##  3 Lincoln Continental kml       4.42
##  4 Chrysler Imperial   kml       6.25
##  5 Camaro Z28          kml       5.65
##  6 Duster 360          mpg      14.3
##  7 Cadillac Fleetwood  mpg      10.4
##  8 Lincoln Continental mpg      10.4
##  9 Chrysler Imperial   mpg      14.7
## 10 Camaro Z28          mpg      13.3
```

from tidyr: pivot_wider() data frames

```
wide_data <- long_data %>%
  pivot_wider(names_from = "variable", values_from = "value")
wide_data
```

```
## # A tibble: 5 x 3
##   name                  kml   mpg
##   <chr>               <dbl> <dbl>
## 1 Duster 360           6.08  14.3
## 2 Cadillac Fleetwood   4.42  10.4
## 3 Lincoln Continental  4.42  10.4
## 4 Chrysler Imperial    6.25  14.7
## 5 Camaro Z28           5.65  13.3
```

```
object.size(wide_data)
```

```
## 1632 bytes
```

```
object.size(long_data)
```

```
## 1992 bytes
```

Using Economic Data (`eurostat` library)

Install and load eurostat

Library to directly download data from Eurostat webpage:
https://ec.europa.eu/eurostat/data/database

More information here:
https://cran.r-project.org/web/packages/eurostat/eurostat.pdf

Cheat sheet here: http://ropengov.github.io/eurostat/articles/website/cheatsheet.html

```
library(eurostat)
```

Preliminary questions

Let's focus on municipal waste by NUTS 2 regions. The name of this data is `env_rwas_gen`

- What is NUTS2? https://en.wikipedia.org/wiki/Regions_of_France
- How can we load it into R?
- What does the dataset contain?
- In which format the data is? Long (tidy, gathered) or wide (non-tidy, spreaded)?

Load the data

You need to understand what you want to (and can) do.

```
eu_waste <- get_eurostat(id = "env_rwas_gen") %>%
  filter(wst_oper == "GEN") %>% # what? waste generated
  filter(unit == "THS_T") %>% # measured how? thousands of tonnes
  filter(time >= "2006-01-01" & time <= "2010-01-01") # when? years in 2005-201

eu_waste
```

```
## # A tibble: 1,149 x 5
##    wst_oper unit  geo   time       values
##    <fct>    <fct> <fct> <date>      <dbl>
##  1 GEN      THS_T AT    2010-01-01  4701.
##  2 GEN      THS_T AT11  2010-01-01   115.
##  3 GEN      THS_T AT12  2010-01-01  1022.
##  4 GEN      THS_T AT13  2010-01-01  1065.
##  5 GEN      THS_T AT21  2010-01-01   243.
##  6 GEN      THS_T AT22  2010-01-01   583.
##  7 GEN      THS_T AT31  2010-01-01   774.
##  8 GEN      THS_T AT32  2010-01-01   312.
##  9 GEN      THS_T AT33  2010-01-01   435.
## 10 GEN      THS_T AT34  2010-01-01   153.
## # ... with 1,139 more rows
```

from dplyr: group_by

Imagine we now want some aggregate information for each region (e.g. the total waste over the years)

```r
eu_waste <- eu_waste %>%
  group_by(geo) %>% # grouping
  mutate(tot_values = sum(values)) %>%
  ungroup() %>% # remember to ungroup (to avoid unindented actions)
  arrange(geo, time) # we can even arrange by two variables at the time

eu_waste
```

```
## # A tibble: 1,149 x 6
##    wst_oper unit   geo   time       values tot_values
##    <fct>    <fct> <fct> <date>      <dbl>      <dbl>
##  1 GEN      THS_T AT    2006-01-01  4932.     24502.
##  2 GEN      THS_T AT    2007-01-01  4951.     24502.
##  3 GEN      THS_T AT    2008-01-01  4997.     24502.
##  4 GEN      THS_T AT    2009-01-01  4921.     24502.
##  5 GEN      THS_T AT    2010-01-01  4701.     24502.
##  6 GEN      THS_T AT11  2006-01-01   112.       598
##  7 GEN      THS_T AT11  2007-01-01   138.       598
##  8 GEN      THS_T AT11  2008-01-01   119.       598
##  9 GEN      THS_T AT11  2009-01-01   115.       598
## 10 GEN      THS_T AT11  2010-01-01   115.       598
## # ... with 1,139 more rows
```

from dplyr: `summarise()`

Imagine we now ONLY want some summary statistics for each region:

- the `max` and `average` waste per region over the years
- the `number of observations` per region

```
eu_waste_sum <- eu_waste %>%
  group_by(geo) %>% # grouping
  summarise(max = max(values),
            mean = mean(values),
            n_obs = n()) %>%
  ungroup()

head(eu_waste_sum)
```

```
## # A tibble: 6 x 4
##   geo     max  mean n_obs
##   <fct> <dbl> <dbl> <int>
## 1 AT    4997. 4900.     5
## 2 AT11   138.  120.     5
## 3 AT12  1070. 1038.     5
## 4 AT13  1204. 1146.     5
## 5 AT21   273.  260.     5
## 6 AT22   638.  615.     5
```

from dplyr: `top_n()`

- which are the top 3 regions with more waste in 2009?
- which are the top 3 regions with less waste in 2009?

```r
eu_waste %>%
  filter(time == "2009-01-01") %>%
  top_n(values, n = 3)
```

```
## # A tibble: 3 x 6
##   wst_oper unit   geo   time        values tot_values
##   <fct>    <fct> <fct> <date>       <dbl>      <dbl>
## 1 GEN      THS_T DE    2009-01-01 37220.    185419.
## 2 GEN      THS_T IT    2009-01-01 32110.    162069.
## 3 GEN      THS_T TR    2009-01-01 30196     148829.
```

```r
eu_waste %>%
  filter(time == "2009-01-01") %>%
  top_n(values, n = -3)
```

```
## # A tibble: 3 x 6
##   wst_oper unit   geo   time        values tot_values
##   <fct>    <fct> <fct> <date>       <dbl>      <dbl>
## 1 GEN      THS_T AT11  2009-01-01  115.         598
## 2 GEN      THS_T ITC2  2009-01-01   79.4        387.
## 3 GEN      THS_T ITF2  2009-01-01  136.         662.
```

Plotting (`ggplot2` library)

What is `ggplot2`

`ggplot2` is a system for declaratively creating graphics, based on *The Grammar of Graphics*.

You provide the data, tell `ggplot2`:

- how to map variables to aesthetics,
- what graphical primitives to use,

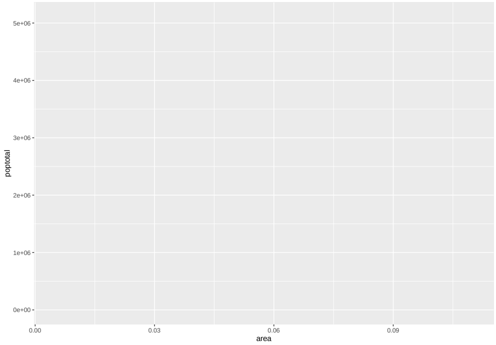
and it takes care of the details.

Look `?ggplot()`

Cheatsheet here:
https://github.com/rstudio/cheatsheets/blob/master/data-visualization-2.1.pdf

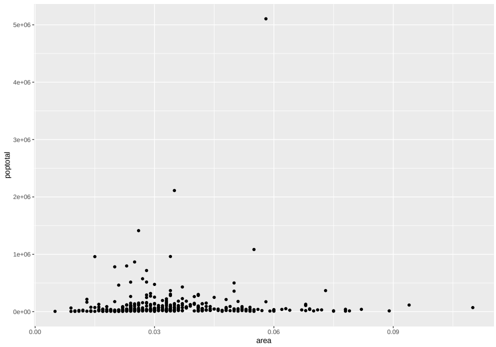
An empty canvas

```r
library(tidyverse)
data("midwest", package = "ggplot2")
ggplot(data = midwest, aes(x = area, y = poptotal))
```



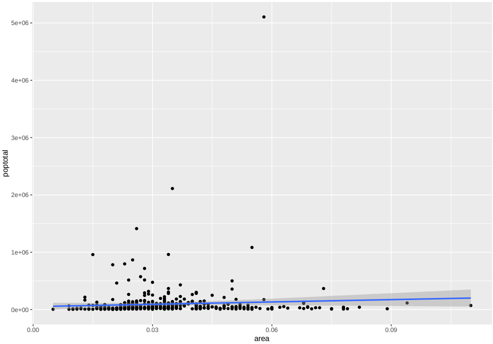
Decide the type of graph (scatter plot)

```
ggplot(data = midwest, aes(x = area, y = poptotal)) +
  geom_point()
```



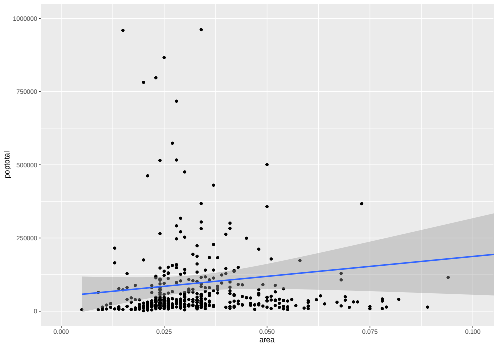
Add the OLS regression line

```r
ggplot(data = midwest, aes(x = area, y = poptotal)) +
  geom_point() +
  geom_smooth(method = "lm")
```



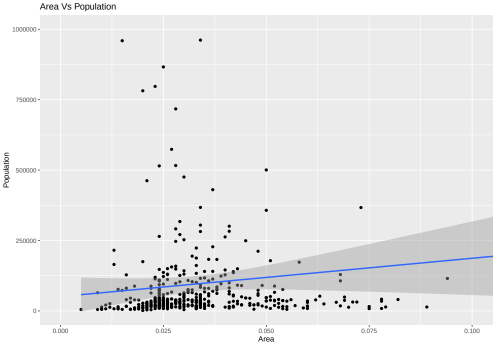
Adjust the axis limits

```r
ggplot(data = midwest, aes(x = area, y = poptotal)) +
  geom_point() +
  geom_smooth(method = "lm") +
  coord_cartesian(xlim=c(0,0.1), ylim=c(0, 1000000))
```



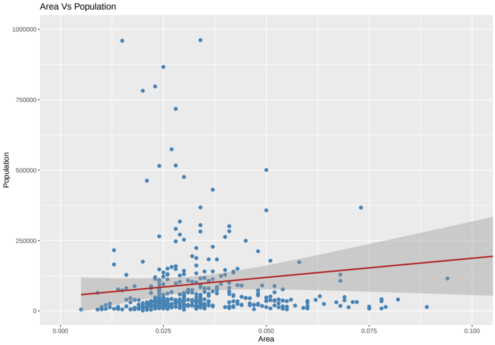
Change axis labels and title

```
ggplot(data = midwest, aes(x = area, y = poptotal)) +
  geom_point() +
  geom_smooth(method = "lm") +
  coord_cartesian(xlim=c(0,0.1), ylim=c(0, 1000000)) +
  ggtitle("Area Vs Population") +
  xlab("Area") +
  ylab("Population")
```



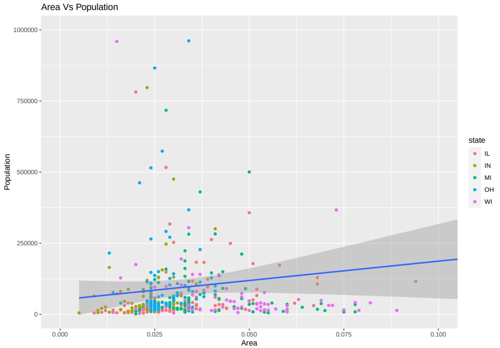
Change colour/size

```
ggplot(data = midwest, aes(x = area, y = poptotal)) +
  geom_point(size = 2, col = "steelblue") +
  geom_smooth(method = "lm", col="firebrick") +
  coord_cartesian(xlim=c(0,0.1), ylim=c(0, 1000000)) +
  ggtitle("Area Vs Population") +
  xlab("Area") +
  ylab("Population")
```



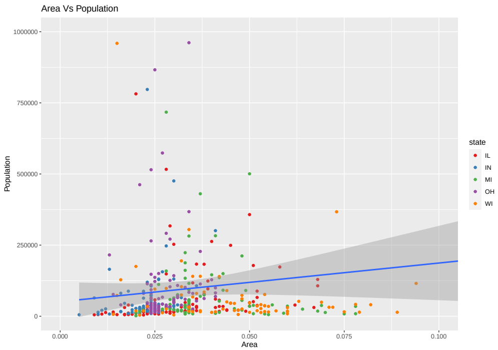
Change colour/size to reflect specific categories

```
ggplot(data = midwest, aes(x = area, y = poptotal)) +
  geom_point(aes(col = state)) +
  geom_smooth(method = "lm") +
  coord_cartesian(xlim=c(0,0.1), ylim=c(0, 1000000)) +
  ggtitle("Area Vs Population") +
  xlab("Area") +
  ylab("Population")
```



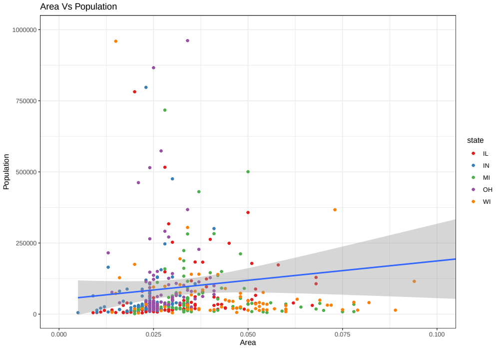
Change colour/size to reflect specific categories (plus color_brewer)

```
library(RColorBrewer)

ggplot(data = midwest, aes(x = area, y = poptotal)) +
  geom_point(aes(col = state)) +
  geom_smooth(method = "lm") +
  coord_cartesian(xlim=c(0,0.1), ylim=c(0, 1000000)) +
  ggtitle("Area Vs Population") +
  xlab("Area") +
  ylab("Population") +
  scale_colour_brewer(palette = "Set1")
```



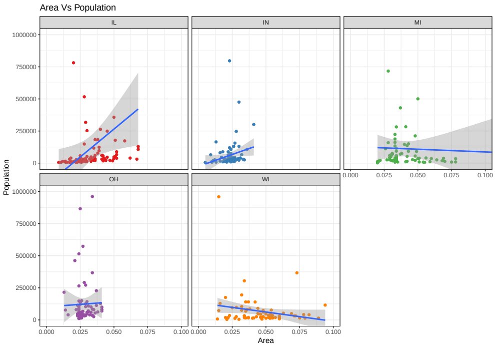
Change theme

```r
library(RColorBrewer)

ggplot(data = midwest, aes(x = area, y = poptotal)) +
  geom_point(aes(col = state)) +
  geom_smooth(method = "lm") +
  coord_cartesian(xlim=c(0,0.1), ylim=c(0, 1000000)) +
  ggtitle("Area Vs Population") +
  xlab("Area") +
  ylab("Population") +
  scale_colour_brewer(palette = "Set1") +
  theme_bw()
```



Grouping and grid

```
ggplot(data = midwest, aes(x = area, y = poptotal)) +
  geom_point(aes(col = state)) +
  geom_smooth(method = "lm") +
  facet_wrap(state~., nrow = 2) +
  coord_cartesian(xlim=c(0,0.1), ylim=c(0, 1000000)) +
  ggtitle("Area Vs Population") +
  xlab("Area") +
  ylab("Population") +
  scale_colour_brewer(palette = "Set1") +
  theme_bw() +
  theme(legend.position = "none")
```



Prepare dataframe for a column plot

```
midwest_state <- midwest %>%
  group_by(state) %>%
  summarise(poptotal = sum(poptotal),
            area = sum(area),
            popdensity = mean(popdensity),
            percwhite = mean(percwhite),
            percblack = mean(percblack),
            percamerindan = mean(percamerindan),
            percasian = mean(percasian),
            percother = mean(percother)) %>%
  ungroup()

midwest_state
```

```
## # A tibble: 5 x 9
##   state poptotal  area popdensity percwhite percblack percamerindan percasia
##   <chr>    <int> <dbl>      <dbl>     <dbl>     <dbl>         <dbl>     <dbl
## 1 IL    11430602  3.30      2824.      95.0     3.65          0.174     0.56
## 2 IN     5544159  2.13      2573.      97.2     1.89          0.222     0.38
## 3 MI     9295297  3.36      3011.      94.4     3.07          1.37      0.50
## 4 OH    10847115  2.42      4639.      95.4     3.51          0.184     0.43
## 5 WI     4891769  3.29      2373.      95.8     0.822         2.52      0.55
## # ... with 1 more variable: percother <dbl>
```

Plot the graph

```
ggplot(data = midwest_state, aes(x = state, y = percasian,
                                 col = state, fill = state)) +
  geom_col(alpha = 0.2) +
  geom_point(size = 5) +
  scale_colour_brewer(palette = "Set1") +
  scale_fill_brewer(palette = "Set1") +
  theme_bw()
```