Learning Data Science in R

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Contents

Foreword

> "Data science is like teenage sex: everyone talks about it, nobody really knows how to do it, everyone thinks everyone else is doing it, so everyone claims they are doing it…"

> — paraphrase of Dan Ariely's quote on big data

There is already a large number of excellent and free references for learning data science in R. The list would be too vast, but two names stand out: Hadley Wickham and Yihui Xie.
Work of the first includes the books Wickham and Grolemund (2016) and Wickham (2014) (freely available, including source code, on github.com/hadley) as well as some of the most popular packages in R such as `ggplot2` (Wickham et al., 2018) and `tidyverse`(Wickham, 2017).
Work of the second is used precisely in the current file thanks to the `rmarkdown` package (Allaire et al., 2018), `knitr` (Xie, 2018b) and `bookdown` (Xie, 2018a). His source code is also on github.com/yihui/.

So, the question arises of why one should even bother to write on the topic. The present "book" is justified on the following grounds.

1. There is no better way of learning data science and R than **doing oneself** the pages of code.

2. The material gathered here is a **personal selection** made on what I judge most relevant for my work, the most important techniques in general or, sometimes, the least obvious for the regular practitioner.

3. These notes serve as a **record** of what I did in the domain so that I can easily access it in the future.

Part I

Getting started

Chapter 1

Getting set

1.1 Install applications

Download the following free applications, available on all platforms:

1. R (https://cran.uni-muenster.de/)
2. RStudio, free Desktop version (https://www.rstudio.com/products/rstudio/download/#download)
3. A Latex distribution (e.g., MacTex for Mac or MiKTeX for Windows machines)

The first two are easily and quickly installed. The last is a very large program (a few Gb) and needs time to install.

Another application needed is a Git (https://git-scm.com/downloads) distribution. This is also a free software.
Once you have installed Git for version control, activate it in RStudio: *Tools> Global Options> Git/SVN* and click on *Enable version control interface for RStudio projects*.
Also generate a SHH RSA key. We will use it to identify at the GitHub repo.

1.2 Sign for GitHub

Create an account at GitHub at https://github.com.

1.3 Create your project

File> New project> Existing Directory and chose that book folder.
Now, every time you create content for your book, you must start a Rstudio session *File> Open Project...*
All the files of the project are the files of the folder, and vice versa.

1.4 Create GitHub repo and link your machine to it

Create a new repository (pronounced 'repo') whose name is **exactly** the same as your R project / book folder (e.g., 'myRbook').
On the top left menu in GitHub, go to *Settings> SHH and GPG keys* and click on 'New SHH key'. Paste the SHH key generated by RStudio.

In RStudio go to *Tools> Project Options...> Git/SVN*. Under *Version control system*, select 'Git'.
Still in RStudio, *Tools> Terminal> New Terminal*. This open a Terminal where you can paste the message shown at the creation of the repo (changing the names, of course):

```
git remote add origin https://github.com/YOURNAME/YOURREPO.git
git push -u origin master
```

Your local `master` should now be connected to the `master` on GitHub.
If necessary, restart RStudio. At the restart, a Git thumbnail should appear in a pane. You are ready to commit and push your files.

Part II

Source file and output files

Chapter 2

Rmd files

This chapter gathers general comments about `.Rmd` files.

2.1 Options for all chuncks

It is convenient to set options for all the R chuncks of the document. This saves time when writing these chuncks.
A natural place to set these options is in a first R chunck.

```
knitr::opts_chunk$set(OPTION1 = TRUE/FALSE,
                      OPTION2 = TRUE/FALSE,
                      ...)
```

Importantly, these options are overriden by the particular chunck options.

```
```{r, OPTION2=FALSE}
```

Options actually take R code. So, the following are examples that could be used to define the option.

```
```{r, eval=4>3, echo=format(Sys.Date(), '%Y-%B-%d') > '2019-March-10'}
# eval is always TRUE
# echo = TRUE if current date is after March 10, 2019
```
```

The list of options can be found here https://yihui.name/knitr/options/. Below are some comments on some of these options (the least trivial for the author).

- `collapse` determines whether the source code and the ouput should be merged into a single block. Here is the same chunck with different values of the option:

`collapse=TRUE`

```
2+ 2
#> [1] 4
3* 5
#> [1] 15
```

`collapse=FALSE`

```
2+ 2
```

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

```
3* 5
```
```

```
#> [1] 15
```

- `comment` gives the string to be printed before the output.

`comment='##'`

```
2+ 2
## [1] 4
```

`comment='R>'`

```
2+ 2
R> [1] 4
```

Worth noting: a `#` as a first character of the comment string (with `collpase=TRUE`) turns the output font into a comment-like text.

- `child` allows a document to call and use another file as input in the document.

```
```{r, child='PATH/TO/OTHER/file.Rmd'}
```

The path can be either absolute or relative.
For relative paths, the following applies:

- `~/` starts a path a the root,
- `../` indicates the parent directory,
- `../../` for parent of the parent directory,
- to move forward, start with the name of the included folder in the current directory.

2.2 Latex code

The overwhelming reason to introduce Latex code in a `.Rmd` file is for typesetting mathematical expressions. There are two main ways to type math in Latex:

- in the text, surrounded by special delimiters, `\( math \)` (alternatively, one can use the deprecated `$ math $`),
- in an equation, surrounded by special delimiters, `\[ math equation \]`, or in a dedicated environment such as `\begin{equation} math equation \end{equation}` (also deprecated, `$$ math equation $$`).

[Complete here with:

. examples of inline code and an equation,
. a reference for Latex,
. maybe the drawing interpreter.]
```

Chapter 3

Customize output

This chapter is about choosing and/or modifying the way the output file looks like.

3.1 Multiple built-in output types

[complete this section] From pdf to slides, through webpages and notebooks.

3.2 New types provided by packages

[complete this section] These are more variations of the above.

3.3 CSS: custom html

A file to change how html outputs look like.

3.4 Latex preamble

This file is added to the preamble of the Latex file to modify how the pdf output is compiled.

Part III

R Basics

Chapter 4

R as a calculator

R can be used as a simple calculator. For instance, 45+17=62 .
Here are a few more examples of the commands.

4.1 Usual operators

4.1.1 Simple operations

The usual symbols `+, -, *, /` apply .

```
2 + 6
#> [1] 8
56/ 6
#> [1] 9.333333
```

4.1.2 Parentheses

The parentheses work as expected. But they are also a common source of error when they are not matched.

```
(4+3)*((7-3)/(1+.05))
#> [1] 26.66667
```

The next expression will generate an error and prevent the compilation of the whole book.

```
(4+3)*((7-3/(1+.05))
```

4.1.3 Exponents

There are two ways of expressing the power of a number: `^` and `**`.

```
3^4
#> [1] 81
3**4
#> [1] 81
```

4.2 Unusual operators

4.2.1 Special operations

The symbols `%/%` and `%%` return the entire part of the result of the division and the rest of the division, respectively.

```
56/6
#> [1] 9.333333
56%/%6
#> [1] 9
56%%6
#> [1] 2
```

4.3 Usual functions

The common functions found in any calculator also have an equivalent on R. The following examples need no further comment.

```
log(100)
#> [1] 4.60517
sqrt(100)
#> [1] 10
```

Part IV

R Basics

Chapter 5

R as a calculator

R can be used as a simple calculator. For instance, 45+17=62 .
Here are a few more examples of the commands.

5.1 Usual operators

5.1.1 Simple operations

The usual symbols `+, -, *, /` apply .

```
2 + 6
#> [1] 8
56/ 6
#> [1] 9.333333
```

5.1.2 Parentheses

The parentheses work as expected. But they are also a common source of error when they are not matched.

```
(4+3)*((7-3)/(1+.05))
#> [1] 26.66667
```

The next expression will generate an error and prevent the compilation of the whole book.

```
(4+3)*((7-3/(1+.05))
```

5.1.3 Exponents

There are two ways of expressing the power of a number: `^` and `**`.

```
3^4
#> [1] 81
3**4
#> [1] 81
```

5.2 Unusual operators

5.2.1 Special operations

The symbols `%/%` and `%%` return the entire part of the result of the division and the rest of the division, respectively.

```
56/6
#> [1] 9.333333
56%/%6
#> [1] 9
56%%6
#> [1] 2
```

5.3 Usual functions

The common functions found in any calculator also have an equivalent on R. The following examples need no further comment.

```
log(100)
#> [1] 4.60517
sqrt(100)
#> [1] 10
```

Chapter 6

Data stuctures

This chapter lists the most common objects to store data.

6.1 Atomic vectors

The basic data structure in R is the vector. Vectors have three characteristics:

- a type, `typeof()`,
- a length, `length()`,
- some attributes, `attributes()`.

6.1.1 Types of data

There are four common types of atomic vectors:

- logical,
- integer,
- double (often called numeric),
- character.

Note that if vector elements not all of the same type, R makes coercion. In that case, the order becomes: "logical < numeric < character".

Here are a few illustrations.

```
log_vector <- c(TRUE, FALSE, FALSE)

int_vector <- c(12, 10, 3, "tre")
typeof(int_vector)
#> [1] "character"
int_vector <- c(12L, 10L, 3L)
typeof(int_vector)
#> [1] "integer"

num_vector <- c(12, 10, 3)
typeof(num_vector)
#> [1] "double"
chr_vector <- c("a", "b", "c")
typeof(chr_vector)
```

```
#> [1] "character"
is.numeric(num_vector)
#> [1] TRUE

no_vector <- c(2, "a")
is.numeric(no_vector)
#> [1] FALSE
typeof(no_vector)
#> [1] "character"
```

```
vector_A <- c(1:5)
vector_A
#> [1] 1 2 3 4 5
length(vector_A)
#> [1] 5
```

6.1.2 Factor vector

This is a special type of vector. It has a limited number of values, called levels. These levels can be unordered (e.g., gender is either "Female" or "Male") or ordered (e.g. school level is "Primary", "Secondary", "Tertiary")

```
gender <-factor(c("Male", "Male", "Female", "Male", "Female", "Female", "Male"))
gender
#> [1] Male   Male   Female Male   Female Female Male
#> Levels: Female Male
levels(gender)
#> [1] "Female" "Male"
summary(gender)
#> Female   Male
#>      3      4
school<-factor(c("Primary", "Secondary", "Tertiary"), ordered=TRUE)
school
#> [1] Primary   Secondary Tertiary
#> Levels: Primary < Secondary < Tertiary

school2<-factor(c("Primary", "Secondary","Secondary", "Tertiary"), labels=c( "Secondary", "Tertiary","Pr
school2
#> [1] Secondary Tertiary  Tertiary  Primary
#> Levels: Secondary < Tertiary < Primary
```

6.2 Matrices and arrays

My experience is that R is not often used for matrices calculations: it is too slow for that, that are better programs for that out there (e.g. Matlab).

```
M <- matrix(c(4, 1, 0, 3, 6, 8), nrow=3, ncol=2)
M
#>      [,1] [,2]
#> [1,]    4    3
#> [2,]    1    6
#> [3,]    0    8
```

If we think of a matrix as a 2 dimensions vector, then arrays are n dimensions vectors. Is it important? Probably in some cases, not so much for us.

```
mya<-array(data=1:18, dim=c(2,3,3))
mya
#> , , 1
#>
#>      [,1] [,2] [,3]
#> [1,]    1    3    5
#> [2,]    2    4    6
#>
#> , , 2
#>
#>      [,1] [,2] [,3]
#> [1,]    7    9   11
#> [2,]    8   10   12
#>
#> , , 3
#>
#>      [,1] [,2] [,3]
#> [1,]   13   15   17
#> [2,]   14   16   18
```

6.3 Lists

These are the one-size fit all structure… A list is an object composed of any other object, even… another list! Very useful data structure!

```
school<-factor(c("Primary", "Secondary", "Tertiary"), ordered=TRUE)
mylist <- list(numbers=c(1:60), somenames=c("Jim","Jules"), results= c(T,F,F,T), school=school)
mylist
#> $numbers
#>  [1]  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
#> [24] 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46
#> [47] 47 48 49 50 51 52 53 54 55 56 57 58 59 60
#>
#> $somenames
#> [1] "Jim"   "Jules"
#>
#> $results
#> [1]  TRUE FALSE FALSE  TRUE
#>
#> $school
#> [1] Primary   Secondary Tertiary
#> Levels: Primary < Secondary < Tertiary
names(mylist) <- c("N", "O","R","S")
```

6.4 Data frames

The second most important data structure in R. You can think of it as a better version of a data set in Excel. It stacks together observations over many variables, each of these variables being a vector.

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

```
mtcars
#>                      mpg cyl  disp  hp drat    wt  qsec vs am gear carb
#> Mazda RX4           21.0   6 160.0 110 3.90 2.620 16.46  0  1    4    4
#> Mazda RX4 Wag       21.0   6 160.0 110 3.90 2.875 17.02  0  1    4    4
#> Datsun 710          22.8   4 108.0  93 3.85 2.320 18.61  1  1    4    1
#> Hornet 4 Drive      21.4   6 258.0 110 3.08 3.215 19.44  1  0    3    1
#> Hornet Sportabout   18.7   8 360.0 175 3.15 3.440 17.02  0  0    3    2
#> Valiant             18.1   6 225.0 105 2.76 3.460 20.22  1  0    3    1
#> Duster 360          14.3   8 360.0 245 3.21 3.570 15.84  0  0    3    4
#> Merc 240D           24.4   4 146.7  62 3.69 3.190 20.00  1  0    4    2
#> Merc 230            22.8   4 140.8  95 3.92 3.150 22.90  1  0    4    2
#> Merc 280            19.2   6 167.6 123 3.92 3.440 18.30  1  0    4    4
#> Merc 280C           17.8   6 167.6 123 3.92 3.440 18.90  1  0    4    4
#> Merc 450SE          16.4   8 275.8 180 3.07 4.070 17.40  0  0    3    3
#> Merc 450SL          17.3   8 275.8 180 3.07 3.730 17.60  0  0    3    3
#> Merc 450SLC         15.2   8 275.8 180 3.07 3.780 18.00  0  0    3    3
#> Cadillac Fleetwood  10.4   8 472.0 205 2.93 5.250 17.98  0  0    3    4
#> Lincoln Continental 10.4   8 460.0 215 3.00 5.424 17.82  0  0    3    4
#> Chrysler Imperial   14.7   8 440.0 230 3.23 5.345 17.42  0  0    3    4
#> Fiat 128            32.4   4  78.7  66 4.08 2.200 19.47  1  1    4    1
#> Honda Civic         30.4   4  75.7  52 4.93 1.615 18.52  1  1    4    2
#> Toyota Corolla      33.9   4  71.1  65 4.22 1.835 19.90  1  1    4    1
#> Toyota Corona       21.5   4 120.1  97 3.70 2.465 20.01  1  0    3    1
#> Dodge Challenger    15.5   8 318.0 150 2.76 3.520 16.87  0  0    3    2
#> AMC Javelin         15.2   8 304.0 150 3.15 3.435 17.30  0  0    3    2
#> Camaro Z28          13.3   8 350.0 245 3.73 3.840 15.41  0  0    3    4
#> Pontiac Firebird    19.2   8 400.0 175 3.08 3.845 17.05  0  0    3    2
#> Fiat X1-9           27.3   4  79.0  66 4.08 1.935 18.90  1  1    4    1
#> Porsche 914-2       26.0   4 120.3  91 4.43 2.140 16.70  0  1    5    2
#> Lotus Europa        30.4   4  95.1 113 3.77 1.513 16.90  1  1    5    2
#> Ford Pantera L      15.8   8 351.0 264 4.22 3.170 14.50  0  1    5    4
#> Ferrari Dino        19.7   6 145.0 175 3.62 2.770 15.50  0  1    5    6
#> Maserati Bora       15.0   8 301.0 335 3.54 3.570 14.60  0  1    5    8
#> Volvo 142E          21.4   4 121.0 109 4.11 2.780 18.60  1  1    4    2
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
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 ...
names(mtcars) # names of the variables in the data frame
#>  [1] "mpg"  "cyl"  "disp" "hp"   "drat" "wt"   "qsec" "vs"   "am"   "gear"
#> [11] "carb"

length(mtcars)
#> [1] 11

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 ...
```

Chapter 7

Simple functions on vectors

In this section, we illustrate calculations with a single vector (element by element) and the recycling rule.

```
visits1 <-  c(12, 2, 45, 75, 65, 11, 3)
visits2 <- c(23, 4, 5, 78, 12, 0, 200)

total <- visits1 + visits2
total
#> [1]  35   6  50 153  77  11 203

total.p2 <- total^2
total.p2
#> [1]  1225    36  2500 23409  5929   121 41209

apples <- 15
bananas <- 60
my.fruits <- apples + bananas
my.fruits
#> [1] 75

l3 <- c(12, 34, 50)
l2 <- c(10, 3)
tt <- l3 + 5
tt
#> [1] 17 39 55

ltotal <- l3+l2 # recycling!!!
#> Warning in l3 + l2: longer object length is not a multiple of shorter
#> object length
```

```
ages <- c(28, 33, 39, 56, 34, 45, 27, 40)
ages
#> [1] 28 33 39 56 34 45 27 40
max(ages)
#> [1] 56
sum(ages)
#> [1] 302
length(ages)
#> [1] 8
```

```
ages <- c(28, 33,39,56,34,45, 27,40, NA)
mean(ages, na.rm=TRUE)
#> [1] 37.75

# for help on a command, simply type ? in front of it
?mean
```

Chapter 8

Subsetting

8.1 Generalities about subsetting

There are three subsetting operators: `$`, `[]` and `[[]]`.
Some functions also allow to create subsets: we'll see that later.
We can combine subsetting and assignment to change some parts of an object.
Complement to `str()`.

```
va <- c(13.1, -15.2, 0.3, 2.4, 10.5, -3.6, 9.7) # create the vector va
str(va)
#>  num [1:7] 13.1 -15.2 0.3 2.4 10.5 -3.6 9.7
```

One can see from this call, that va is a simple vector with r length(va) elements. Subsetting means chosing among these.

8.2 `[]`

Applies to vectors, matrices, lists and data frames.
Can be used with:

```
- positive or negative values,
- many values in a vector,
- logical, `NA`,
- character vectors when names.
```

8.2.1 On a vector

Here are a few examples of that object used on a vector.

```
va <- c(13.1, -15.2, 0.3, 2.4, 10.5, -3.6, 9.7)
va[1] # element 1
#> [1] 13.1
va[c(3:5)] # elements 3 to 5
#> [1]  0.3  2.4 10.5
va[-1] # all elements minus the element 1
#> [1] -15.2   0.3   2.4  10.5  -3.6   9.7
va[c(TRUE,TRUE,TRUE,FALSE,FALSE,TRUE,FALSE)]
```

```
#> [1]  13.1 -15.2   0.3  -3.6
va[c(TRUE,FALSE)] # notice the recycling at play here
#> [1] 13.1  0.3 10.5  9.7
va[NA]
#> [1] NA NA NA NA NA NA NA
va[] # nothing selected gives the full vector
#> [1]  13.1 -15.2   0.3   2.4  10.5  -3.6   9.7
names(va)<-letters[1:length(va)] # give names to va
# notice that we subset the vector letters (given by R) and that we don't
# specify the length but give a general value
# now we can subset using names
va
#>     a     b     c     d     e     f     g
#>  13.1 -15.2   0.3   2.4  10.5  -3.6   9.7
va[c("a","e","b")]
#>     a     e     b
#>  13.1  10.5 -15.2
```

8.2.2 On a list

```
mylist<- list(numbers=c(1:20),
              ournames=c("Jim","Jules"),
              results= c(T,F,F,T),
              school=factor(c("Primary", "Secondary", "Tertiary"), ordered=TRUE))
str(mylist)
#> List of 4
#>  $ numbers : int [1:20] 1 2 3 4 5 6 7 8 9 10 ...
#>  $ ournames: chr [1:2] "Jim" "Jules"
#>  $ results : logi [1:4] TRUE FALSE FALSE TRUE
#>  $ school  : Ord.factor w/ 3 levels "Primary"<"Secondary"<..: 1 2 3

mylist[1] # first element of the list
#> $numbers
#>  [1]  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20
class(mylist[1])
#> [1] "list"
mylist[[3]][3]
#> [1] FALSE
```

Notice that the result of this subsetting is a r class(mylist[1])!

8.2.3 On a matrix

```
set.seed(42)
my.mat <- matrix(floor(runif(30)*10), nrow=5)
my.mat
#>      [,1] [,2] [,3] [,4] [,5] [,6]
#> [1,]    9    5    4    9    9    5
#> [2,]    9    7    7    9    1    3
#> [3,]    2    1    9    1    9    9
#> [4,]    8    6    2    4    9    4
#> [5,]    6    7    4    5    0    8
str(my.mat)
```

```
#>  num [1:5, 1:6] 9 9 2 8 6 5 7 1 6 7 ...
length(my.mat)
#> [1] 30
```

The structure shows that there are r length(dim(my.mat)) dimensions. For subsetting, we must give r length(dim(my.mat)) dimensions! Same rules as for the vectors apply.

```
my.mat[2,3] # 2nd row, 3rd row
#> [1] 7
my.mat[-1,]
#>      [,1] [,2] [,3] [,4] [,5] [,6]
#> [1,]    9    7    7    9    1    3
#> [2,]    2    1    9    1    9    9
#> [3,]    8    6    2    4    9    4
#> [4,]    6    7    4    5    0    8
colnames(my.mat) <- letters[1:ncol(my.mat)] # give names to the columns
rownames(my.mat) <- LETTERS[1:nrow(my.mat)] # give names to the rows
my.mat
#>   a b c d e f
#> A 9 5 4 9 9 5
#> B 9 7 7 9 1 3
#> C 2 1 9 1 9 9
#> D 8 6 2 4 9 4
#> E 6 7 4 5 0 8
my.mat["C",c("a","c","e")]
#> a c e
#> 2 9 9
```

8.3 [[]]

This object is used mainly for lists.

```
mylist<- list(numbers=c(1:20),
              ournames=c("Jim","Jules"),
              results= c(T,F,F,T),
              school=factor(c("Primary", "Secondary", "Tertiary"), ordered=TRUE))
str(mylist)
#> List of 4
#>  $ numbers : int [1:20] 1 2 3 4 5 6 7 8 9 10 ...
#>  $ ournames: chr [1:2] "Jim" "Jules"
#>  $ results : logi [1:4] TRUE FALSE FALSE TRUE
#>  $ school  : Ord.factor w/ 3 levels "Primary"<"Secondary"<..: 1 2 3
mylist[[1]]
#>  [1]  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20
```

8.4 $

This object is usually for data frames, where it gives the variable.
It allows partial matching (e.g., `mtcars$gear` is the same as `mtcars$gea`)

```
data(mtcars)
names(mtcars)
#>  [1] "mpg"  "cyl"  "disp" "hp"   "drat" "wt"   "qsec" "vs"   "am"   "gear"
```

```
#> [11] "carb"
mtcars$mpg
#>  [1] 21.0 21.0 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 17.8 16.4 17.3 15.2
#> [15] 10.4 10.4 14.7 32.4 30.4 33.9 21.5 15.5 15.2 13.3 19.2 27.3 26.0 30.4
#> [29] 15.8 19.7 15.0 21.4
mtcars[["mpg"]] # just exactly the same, but R users prefer the $
#>  [1] 21.0 21.0 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 17.8 16.4 17.3 15.2
#> [15] 10.4 10.4 14.7 32.4 30.4 33.9 21.5 15.5 15.2 13.3 19.2 27.3 26.0 30.4
#> [29] 15.8 19.7 15.0 21.4
mtcars["mpg"] # NOT the same at all! [] preserves the class
#>                      mpg
#> Mazda RX4           21.0
#> Mazda RX4 Wag       21.0
#> Datsun 710          22.8
#> Hornet 4 Drive      21.4
#> Hornet Sportabout   18.7
#> Valiant             18.1
#> Duster 360          14.3
#> Merc 240D           24.4
#> Merc 230            22.8
#> Merc 280            19.2
#> Merc 280C           17.8
#> Merc 450SE          16.4
#> Merc 450SL          17.3
#> Merc 450SLC         15.2
#> Cadillac Fleetwood  10.4
#> Lincoln Continental 10.4
#> Chrysler Imperial   14.7
#> Fiat 128            32.4
#> Honda Civic         30.4
#> Toyota Corolla      33.9
#> Toyota Corona       21.5
#> Dodge Challenger    15.5
#> AMC Javelin         15.2
#> Camaro Z28          13.3
#> Pontiac Firebird    19.2
#> Fiat X1-9           27.3
#> Porsche 914-2       26.0
#> Lotus Europa        30.4
#> Ford Pantera L      15.8
#> Ferrari Dino        19.7
#> Maserati Bora       15.0
#> Volvo 142E          21.4
class(mtcars["mpg"])
#> [1] "data.frame"
```

8.5 Combining subsetting

Notice that we can often subset further until having the desired subset. Here are a few examples.

```
mtcars$mpg[1:4]
#> [1] 21.0 21.0 22.8 21.4
mylist[["ournames"]][1]
```

```
#> [1] "Jim"
mylist$ournames[1]
#> [1] "Jim"
```

8.6 Subsetting with one condition

We can use conditions for subsetting

```
mtcars[mtcars$cyl==8,]
#>                      mpg cyl  disp  hp drat    wt  qsec vs am gear carb
#> Hornet Sportabout   18.7   8 360.0 175 3.15 3.440 17.02  0  0    3    2
#> Duster 360          14.3   8 360.0 245 3.21 3.570 15.84  0  0    3    4
#> Merc 450SE          16.4   8 275.8 180 3.07 4.070 17.40  0  0    3    3
#> Merc 450SL          17.3   8 275.8 180 3.07 3.730 17.60  0  0    3    3
#> Merc 450SLC         15.2   8 275.8 180 3.07 3.780 18.00  0  0    3    3
#> Cadillac Fleetwood  10.4   8 472.0 205 2.93 5.250 17.98  0  0    3    4
#> Lincoln Continental 10.4   8 460.0 215 3.00 5.424 17.82  0  0    3    4
#> Chrysler Imperial   14.7   8 440.0 230 3.23 5.345 17.42  0  0    3    4
#> Dodge Challenger    15.5   8 318.0 150 2.76 3.520 16.87  0  0    3    2
#> AMC Javelin         15.2   8 304.0 150 3.15 3.435 17.30  0  0    3    2
#> Camaro Z28          13.3   8 350.0 245 3.73 3.840 15.41  0  0    3    4
#> Pontiac Firebird    19.2   8 400.0 175 3.08 3.845 17.05  0  0    3    2
#> Ford Pantera L      15.8   8 351.0 264 4.22 3.170 14.50  0  1    5    4
#> Maserati Bora       15.0   8 301.0 335 3.54 3.570 14.60  0  1    5    8
mtcars[mtcars$cyl==8 & mtcars$carb==4,]
#>                      mpg cyl disp  hp drat    wt  qsec vs am gear carb
#> Duster 360          14.3   8  360 245 3.21 3.570 15.84  0  0    3    4
#> Cadillac Fleetwood  10.4   8  472 205 2.93 5.250 17.98  0  0    3    4
#> Lincoln Continental 10.4   8  460 215 3.00 5.424 17.82  0  0    3    4
#> Chrysler Imperial   14.7   8  440 230 3.23 5.345 17.42  0  0    3    4
#> Camaro Z28          13.3   8  350 245 3.73 3.840 15.41  0  0    3    4
#> Ford Pantera L      15.8   8  351 264 4.22 3.170 14.50  0  1    5    4
mtcars[mtcars$cyl==8, c("cyl", "mpg", "wt")]
#>                     cyl  mpg    wt
#> Hornet Sportabout     8 18.7 3.440
#> Duster 360            8 14.3 3.570
#> Merc 450SE            8 16.4 4.070
#> Merc 450SL            8 17.3 3.730
#> Merc 450SLC           8 15.2 3.780
#> Cadillac Fleetwood    8 10.4 5.250
#> Lincoln Continental   8 10.4 5.424
#> Chrysler Imperial     8 14.7 5.345
#> Dodge Challenger      8 15.5 3.520
#> AMC Javelin           8 15.2 3.435
#> Camaro Z28            8 13.3 3.840
#> Pontiac Firebird      8 19.2 3.845
#> Ford Pantera L        8 15.8 3.170
#> Maserati Bora         8 15.0 3.570
```

8.7 Subsetting and assignment

Subsetting can be used to change a part of an object through assignment. Assign `NULL` to delete subset

```
my.mat
#>   a b c d e f
#> A 9 5 4 9 9 5
#> B 9 7 7 9 1 3
#> C 2 1 9 1 9 9
#> D 8 6 2 4 9 4
#> E 6 7 4 5 0 8
my.mat[,1]<-1:nrow(my.mat)
my.mat
#>   a b c d e f
#> A 1 5 4 9 9 5
#> B 2 7 7 9 1 3
#> C 3 1 9 1 9 9
#> D 4 6 2 4 9 4
#> E 5 7 4 5 0 8
mtcars$mpg[1]<-1234
names(mtcars)
#>  [1] "mpg"  "cyl"  "disp" "hp"   "drat" "wt"   "qsec" "vs"   "am"   "gear"
#> [11] "carb"
mtcars$drat<-NULL # delete variable drat in data frame mtcars
# does not delete in matrix
names(mtcars)
#>  [1] "mpg"  "cyl"  "disp" "hp"   "wt"   "qsec" "vs"   "am"   "gear" "carb"
```

8.8 Using `which()`

`which()` gives the integers that correspond to the boolean (logical) `TRUE`.
This can help subsetting

```
vb<-1500:1530
vb
#>  [1] 1500 1501 1502 1503 1504 1505 1506 1507 1508 1509 1510 1511 1512 1513
#> [15] 1514 1515 1516 1517 1518 1519 1520 1521 1522 1523 1524 1525 1526 1527
#> [29] 1528 1529 1530
which(vb%%5==0) # which is divisible by 5 (modulo is 0) ?
#> [1]  1  6 11 16 21 26 31
# notice that this is asking each element of vb,
# which() reports the positions for which the answer is TRUE
vb[which(vb%%5==0)]
#> [1] 1500 1505 1510 1515 1520 1525 1530
```

8.9 More advanced stuff

8.9.1 Difference between simplifying and preserving

We say ‘preserve’ to say the same structure is maintained when subsetting (e.g., a subset of a data frame remains a data frame).

Simplifying does not keep the structure but gives the simplest output possible.
`drop` argument allows to preserve (`drop=FALSE`) or not (`drop= TRUE`).
`[]` usually preserves, `[[]]` usually simplifies.
To better understand, check the classes:

```
all.equal(class(mylist[1]), class(mylist[[1]]))
#> [1] "1 string mismatch"
class(mylist[1])
#> [1] "list"
class(mylist[[1]])
#> [1] "integer"
all.equal(class(mylist), class(mylist[1]))
#> [1] TRUE
all.equal(class(mylist), class(mylist[[1]]))
#> [1] "1 string mismatch"
```

We see that `[]` has preserved the class of `mylist` (r class(mylist)), while `[[]]` has not! Another striking example is the following.

```
ma2 <- my.mat[1:2,1:3]
class(ma2)
#> [1] "matrix"
ma3 <- my.mat[1,1:3]
class(ma3)
#> [1] "numeric"
```

`ma3` is NOT a matrix anymore!!! This is because one of its dimensions is 1. Losing track of the class when subsetting can generate lots of problems in the middle of a large code. And it is a common source of error! To be sure of keeping the class, we can use `drop=FALSE` (the class will not be dropped to, usually, a vector).

```
ma4 <- my.mat[1,1:3, drop=FALSE]
ma4
#>   a b c
#> A 1 5 4
class(ma4)
#> [1] "matrix"
```

Chapter 9

Conditions

The general purpose of conditions is to control the flow of our code when executed by R.
In R, it builds on statements such as `if` and `else`.

9.1 `if` statement

The simplest form for a condition uses a `if` statement.
The form is then:

```
if (condition) {
# code to be executed if the condition is met
}
```

The key point is that R will run the code until it finds a condition that is met. If it doesn't find any, it continues to the next lines of code.
Here is an example.

```
gains <- c(10, 3,-5,0,-4,12,4)
sum(gains)
#> [1] 20
if (sum(gains) > 0) {
  print("Congratulations, you are winning!")
}
#> [1] "Congratulations, you are winning!"

gains[1] <- -10 # change the first element of gains
if (sum(gains) > 0) {
  print("Congratulations, you are winning!")
} # notice that there is no output, because the condition was not met
```

9.2 `else` statement

What happens when the condition is not met? It's on the user to decide. It can be nothing or… something else!

```
if (condition) {
# code to be executed if the condition is met
} else {
```

```
# code to be executed if the condition is NOT met
}
```

Here is an example.

```
gains<- c(10, 3,-5,0,-4,12,4)
gains[1] <- -10 # change the first element of gains
sum(gains)
#> [1] 0
if (sum(gains) > 0) {
  print("Congratulations, you are winning!")
} else {
  print("You are not winning!")
} # notice that now there is an output!
#> [1] "You are not winning!"
```

9.3 else if statement

`else if` allows us to introduce another condition to our flow of code

```
if (condition_1) {
# code to be executed if the condition_1 is met
} else if (condition_2) {
# code to be executed if the condition_2 is met
} else {
# code to be executed if NEITHER condition_1 NOR condition_2 is met
}
```

We can use as many `else if` statements as we want.
Here is an example with only one `else if`

```
gains<- c(10, 3,-5,0,-4,12,4)
gains[1] <- -10 # change the first element of gains
sum(gains)
#> [1] 0
if (sum(gains) > 0) {
  print("Congratulations, you are winning!")
} else if (sum(gains)==0) {
  print("You just break even!")
} else {
  print("You are losing!")
}
#> [1] "You just break even!"
```

Notice the potential problem of not putting a `else` statement at the end of the conditions system.

9.4 ifelse statement

For **short** conditions, we can use `ifelse`.
The form is

```
ifelse(condition, value if condition met, value if value not met)
```

Here is an example.

```
gains <- c(10, 3,-5,0,-4,12,4)
sign <- ifelse(sum(gains)>=0,"+","-")
sign
#> [1] "+"
```

9.5 Logical operators: &, | and !

Logical operators are used to combine, mix or negate several conditions: - & means AND - | means OR - ! means NOT

De Morgan's laws may help here.

```
(10%%2==0 & 27%%3==0) # equivalent to (TRUE and TRUE), hence TRUE
#> [1] TRUE
TRUE & FALSE
#> [1] FALSE
!TRUE
#> [1] FALSE
!(TRUE & TRUE)
#> [1] FALSE
!(TRUE & !TRUE)
#> [1] TRUE
((10%%2==0 & 27%%2==0)) # equivalent to (TRUE and FALSE), hence FALSE
#> [1] FALSE
((10%%2==0 | 27%%2==0)) # equivalent to (TRUE or FALSE), hence TRUE
#> [1] TRUE
```

9.6 Writing and interpreting a condition

Notice that what R looks for in a condition is a either a TRUE or a FALSE.
If it encounters a TRUE, it executes the commands, otherwise, it doesn't.
Remember there are many ways to obtain one of these two logicals.
Any of these ways will work as a condition.
Here are examples of less trivial ways of writing a condition

```
gains<- c(10, 3,-5,0,-4,12,4)

if (is.numeric(gains)) {
  print("Seems like it is a numeric vector...")
}
#> [1] "Seems like it is a numeric vector..."
# here, is.numeric(gains) evaluates to TRUE, hence, the code is executed!
# the beginner's way would be to replace the condition by
# if (class(gains)=="numeric")

if (!is.factor(gains)) {
  print("Yeah! We avoided the factor...")
}
#> [1] "Yeah! We avoided the factor..."
# the beginner would write if (class(gains)!="factor")
```

Chapter 10

Conclusion

We did a great book!

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