



# SC-Camp 2016

## Introduction to R and Data Analysis

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**Joseph Emeras**

ANEC, Luxembourg  
(Formerly University of Luxembourg)



# Summary

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## 1 Introduction to R

## 2 Practical Session

- Pre-requisites

- Objectives

- Practical Session Details



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# R?

R (pronounced aRgh – pirate style) is a programming language and environment for statistical computing and graphics

- oriented towards data handling analysis and storage facility
- R Base
- Packages tools and functions (user contributed)
- R Base and most R packages are available from the [Comprehensive R Archive Network \(CRAN\)](#)
- Use R console or IDE: **Rstudio**, Deducer, vim/emacs...
- Comment is #, help is ? before a function name



## Using R

### Installing/using packages

Install and load the ggplot2 package (even if already installed)

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

Or in one step, install if not available then load:

```
require(ggplot2) || {install.packages("ggplot2");  
                      require(ggplot2)}
```



## Numbers in R: NaN and NA

- NaN (not a number)
- NA (missing value)

Basic handling of missing values

```
> x  
[1] 1 2 3 4 5 6 7 8 NA  
> mean(x)  
[1] NA  
> mean(x, na.rm=TRUE)  
[1] 4.5
```



## Objects in R

Objects in R obtain values by assignment.

This is achieved by the gets arrow, `<-`, or the equal sign, `=`.

Objects can be of different kinds.



## Data Structures

- scalar:

```
s = 3.14
```

- vector:

```
v = c(1, 2, "ron")
```

- list:

```
l = list(1:10, 'a', pi)
```

- matrix:

```
m = matrix(seq(1:6), 2)
```

- **dataframe:**

```
df = data.frame("col1" = seq(1:4), "col2" = c(5, 6, "cerveza", 6*7))
```

- ...





## Functions

Functions are created using the `function()` directive and are stored as R objects just like anything else. In particular, they are R objects of class “function”.

```
f <- function(<arguments>) {  
## Do something interesting  
}
```

Functions in R are “first class objects”, which means that they can be treated much like any other R object.

The return value of a function is the last expression in the function body to be evaluated.



## Arguments

R functions arguments can be matched positionally or by name. So the following calls to `sd` are all equivalent

```
> mydata <- rnorm(100)
> sd(mydata)
> sd(x = mydata)
> sd(x = mydata, na.rm = FALSE)
> sd(na.rm = FALSE, x = mydata)
> sd(na.rm = FALSE, mydata)
```

Even though it's legal, I don't recommend messing around with the order of the arguments too much, since it can lead to some confusion.



## Argument Matching

You can mix positional matching with matching by name. When an argument is matched by name, it is “taken out” of the argument list and the remaining unnamed arguments are matched in the order that they are listed in the function definition.

e.g. The following two calls are equivalent.

```
lm(data = mydata, y ~ x, model = FALSE, 1:100)
```

```
lm(y ~ x, mydata, 1:100, model = FALSE)
```



## Argument Matching

- Most of the time, named arguments are useful on the command line when you have a long argument list and you want to use the defaults for everything except for an argument near the end of the list
- Named arguments also help if you can remember the name of the argument and not its position on the argument list (plotting is a good example).



## Defining a Function

```
f <- function(a, b = 1, c = 2, d = NULL) {  
}
```

In addition to not specifying a default value, you can also set an argument value to NULL.



## Lazy Evaluation

Arguments to functions are evaluated lazily, so they are evaluated only as needed.

```
f <- function(a, b) {  
  a^2  
}  
f(2)
```

This function never actually uses the argument `b`, so calling `f(2)` will not produce an error because the `2` gets positionally matched to `a`.



## Lazy Evaluation

Another example

```
f <- function(a, b) {  
  print(a)  
  print(b)  
}
```

```
> f(45)
```

```
[1] 45
```

```
Error in print(b) : argument "b" is missing,  
with no default
```

```
>
```

Notice that “45” got printed first before the error was triggered. This is because `b` did not have to be evaluated until after `print(a)`. Once the function tried to evaluate `print(b)` it had to throw an error.



# Using R

## Usefull Functions

- List all objects in memory: `ls()`
- Save an object: `save(obj, file)`
- Load an object: `load(file)`
- Set working directory: `setwd(dir)`





## Entering Data

### Reading CSV or text files

```
# comma separated values
dat.csv <- read.csv(<file or url>)
# tab separated values
dat.tab <- read.table(<file or url>,
  header=TRUE, sep = "\t")
```



## Entering Data

### Reading data from other software: Excel, SPSS...

Excel Spreadsheets – need `xlsx` package

```
read.xlsx()
```

SPSS and Stata both need the `foreign` package

```
dat.spss <- read.spss(<file or url>,  
                      to.data.frame=TRUE)
```

```
dat.dta <- read.dta(<file or url>)
```



## Data Frames

Most easy structure to use, have a matrix structure.

- **Observations** are arranged as **rows** and **variables**, either numerical or categorical, are arranged as **columns**.
- Individual rows, columns, and cells in a data frame can be accessed through many methods of indexing.
- We most commonly use **object[*row*,*column*]** notation.



## Accessing Items in a data.frame

Aside with R are provided example datasets, i.e. `mtcars` that can be used

```
data(mtcars)
```

```
head(mtcars)
```

```
colnames(mtcars)
```

```
# single cell value
```

```
mtcars[2,3]
```

```
# omitting row value implies all rows
```

```
mtcars[,3]
```

```
# omitting column values implies all columns
```

```
mtcars[2,]
```



## Accessing Items in a data.frame

We can also access variables directly by using their names, either with **object[,"variable"]** notation or **object\$variable** notation.

```
# get first 10 rows of variable 'mpg' using two methods:  
mtcars[1:10, "mpg"]  
mtcars$mpg[1:10]
```



# Exploring Data

## Description Of Dataset

- Using **dim**, we get the number of observations(rows) and variables(columns) in the dataset.  
`dim(mtcars)`
- Using **str**, we get the structure of the dataset, including the class(type) of all variables.  
`str(mtcars)`
- **summary** when used on a dataset, returns distributional summaries of variables in the dataset.  
`summary(mtcars)`
- **quantile** function enables to get statistical metrics on the selected data  
`quantile(mtcars$mpg)`



# Exploring Data

## Conditional Exploration

- **subset** enables to explore data conditionally  
`subset(mtcars, cyl <= 5)`
- **by** enables to call a particular function to sub-groups of data  
`by(mtcars, mtcars$cyl, summary)`



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# Install and Run R

## 1 On your local machine:

- Find a release that fits your distribution at CRAN Archive
- Install and launch R-Studio

<http://cran.r-project.org/>

<https://www.rstudio.com/>

## 2 On the cluster

First connect to the cluster, then submit a job to run R.

```
(localhost)$> ssh cluster  
(frontend)$> oarsub -I -l core=1,walltime="00:30:00"  
(node)$> R
```

## 3 Install and Load a Package

```
(R-shell)$> install.packages("ggplot2")  
(R-shell)$> library(ggplot2)
```



## Objectives of this Practical Session

- Being able to plot data
  - histogram for data distribution
  - plot in different colors from different data sources
- Know some tips to organize your data
  - aggregate a dataset by column and apply an aggregation function
  - data.table package for binary search in datasets
  - performance in R operations
- R in parallel
  - on one machine
  - on a cluster with socket communications
  - MPI communications



## Exercises

- Start the tutorial <https://github.com/sc-camp/camp2016>
  - Plot 2 graphs in section Simple Plotting
  - Answer 2 questions at the end of section Organizing your Data
  - Compare performance of aggregation operations w/wo parallelization
- Plot a speedup graph
  - with different number of cores and/or machines
  - needs: ggplot, parallel R



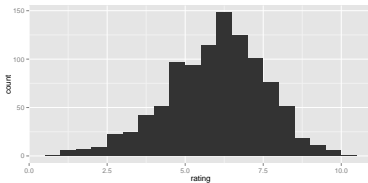
## After the Practical Session: Problems

- regression models: example and exercise
- parallelization of K-means Clustering: example and exercise

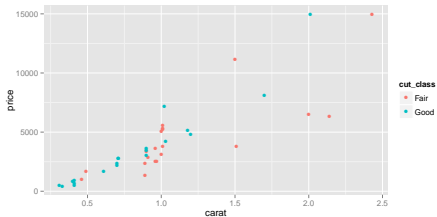


# Simple Plotting

Movies Histogram:



Diamonds Plot with 2 colours:





## PS Questions

**Question: use ddply instead of tapply in the first example**

```
ddply(DT, .(x), summarize, sum(v))
```

**Question: return the min and max instead of the sum.**

```
min_max = function(data){  
  c(min(data), max(data))  
}  
DT[,min_max(v),by=x]  
  
## or  
DT[,c(min(v), max(v)),by=x]
```



Thank you for your attention...

## Questions?



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Thank you for your attention...

## Usefull links

- CRAN Archive <http://cran.r-project.org/>
- ggplot2 Documentation <http://docs.ggplot2.org/current/>
- CRAN HPC Packages <http://cran.r-project.org/web/views/HighPerformanceComputing.html>
- Advanced R programming by Hadley Wickham <http://adv-r.had.co.nz/>