



Clase 1: Introducción al programa

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Agenda

1. Descargando e instalando el software

2. Qué nos ofrece este software?

3. Lo que debemos saber

4. Manipulación de datos



Agenda

1. Descargando e instalando el software



Pasos para la descarga:

- 1. Descarga R
- 2. Instala R
- 3. Descarga RStudio
- 4. Instala RStudio













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The Comprehensive R Archive Network

Download and Install R

Precompiled binary distributions of the base system and contributed packages, **Windows and Mac** users most likely want one of these versions of R:

- Download R for Linux
- Download R for (Mac) OS X
- Download R for Windows

R is part of many Linux distributions, you should check with your Linux package management system in addition to the link above.

Source Code for all Platforms

Windows and Mac users most likely want to download the precompiled binaries listed in the upper box, not the source code. The sources have to be compiled before you can use them. If you do not know what this means, you probably do not want to do it!

- The latest release (2020-06-22, Taking Off Again) R-4.0.2.tar.gz, read what's new in the latest version.
- Sources of R alpha and beta releases (daily snapshots, created only in time periods before a planned release).
- Daily snapshots of current patched and development versions are <u>available here</u>. Please read about <u>new features</u>
 and <u>bug fixes</u> before filing corresponding feature requests or bug reports.
- Source code of older versions of R is available here.
- Contributed extension <u>packages</u>

Questions About R

• If you have questions about R like how to download and install the software, or what the license terms are, please





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Manuals FAQs Contributed Subdirectories:

<u>base</u> Binaries for base distribution. This is what you want to <u>install R for the first time</u>.

Binaries of contributed CRAN packages (for R >= 2.13.x; managed by Uwe Ligges). There is also information contrib on third party software available for CRAN Windows services and corresponding environment and make

variables.

old contrib

Binaries of contributed CRAN packages for outdated versions of R (for R < 2.13.x; managed by Uwe Ligges).

Tools to build R and R packages. This is what you want to build your own packages on Windows, or to build R

Rtools itself.

Please do not submit binaries to CRAN. Package developers might want to contact Uwe Ligges directly in case of questions / suggestions related to Windows binaries.

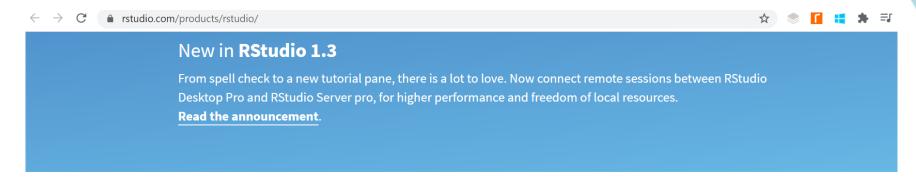
R for Windows

You may also want to read the RFAQ and R for Windows FAQ.

Note: CRAN does some checks on these binaries for viruses, but cannot give guarantees. Use the normal precautions with downloaded executables.



Una vez que tenemos el software R instalado, procedemos à instalar RStudio



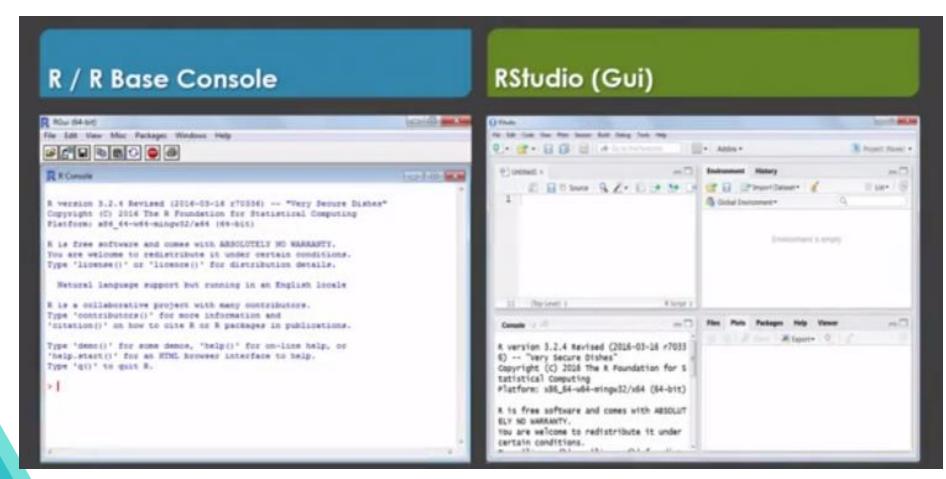
There are two versions of RStudio:







Una vez que tenemos el software R instalado, procedemos a instalar RStudio





Agenda

2. Qué nos ofrece este software?

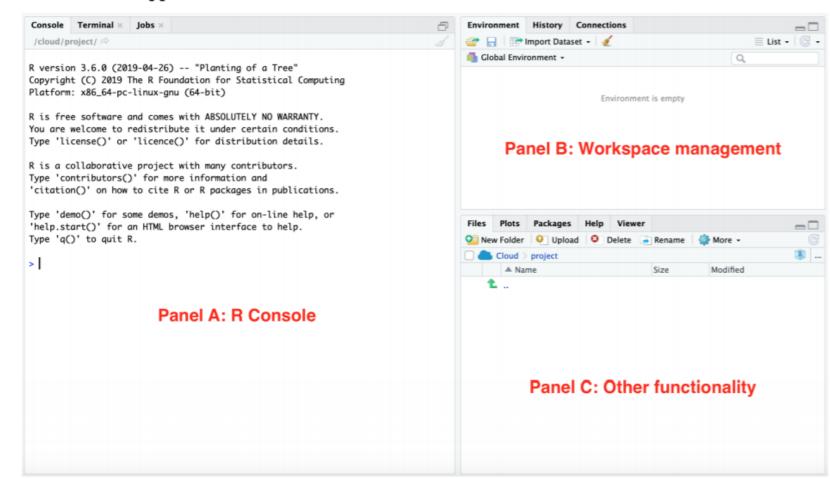


2. Qué nos ofrece software?

RStudio ofrece:

- 1. Es un fuerte de editor de código que soporta la ejecución de código.
- 2. Manejo del workspace
- 3. Debugging, syntaxhighlighting, permite completa el código de forma inteligente
- 4. Fácil comunicación con otros softwares y plataformas

RStudio application





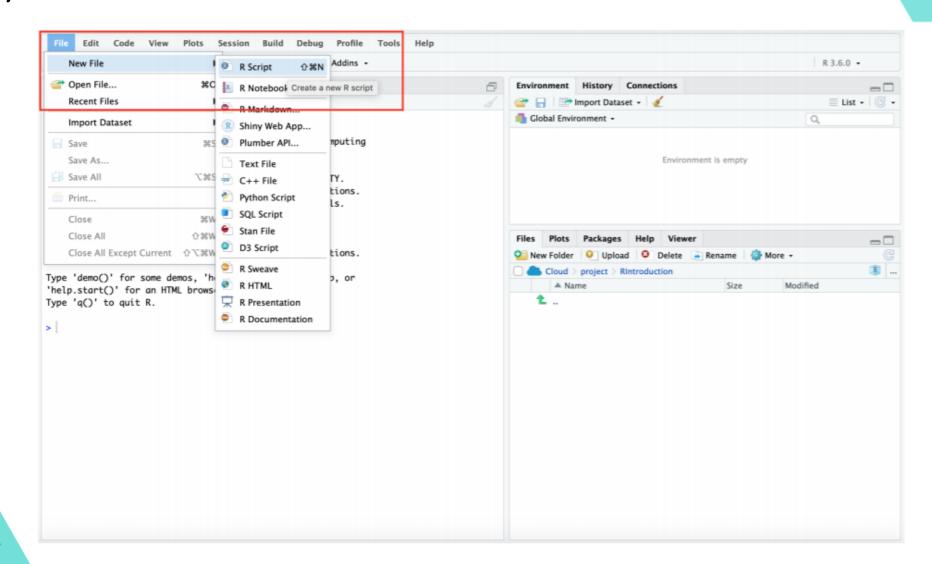
La secuencia de comandos necesaria para análisis es típicamente escrito en textfiles antes de su ejecución.

Ventajas:

- Documentación de tareas
- Automatización de tareas repetitivas
- Evaluación de cambios



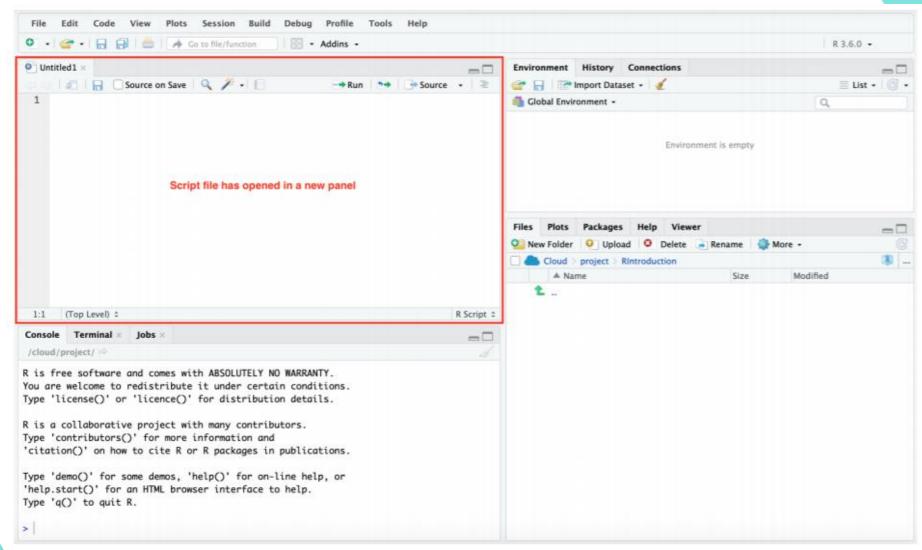
Script (.R) Paso 1: Creamos un script file





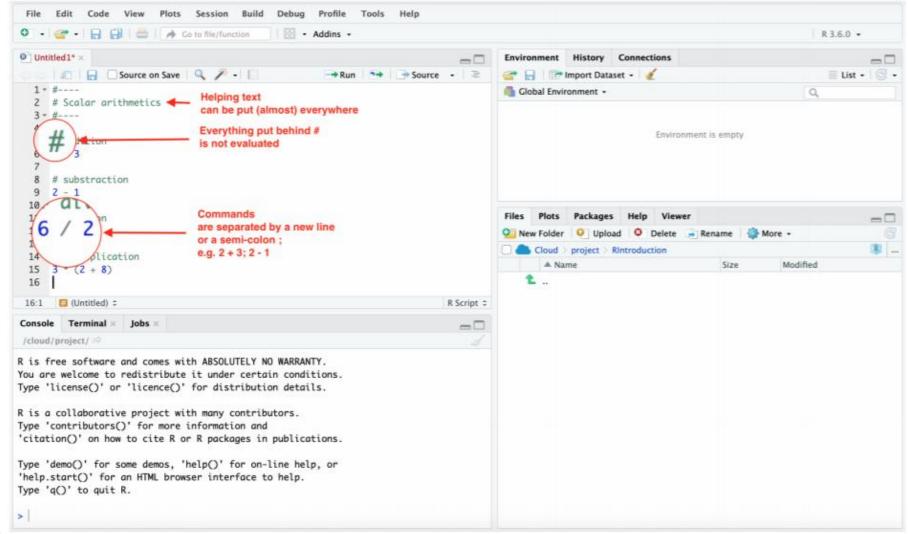
Script (.R)

Paso 2: Creamos un script file



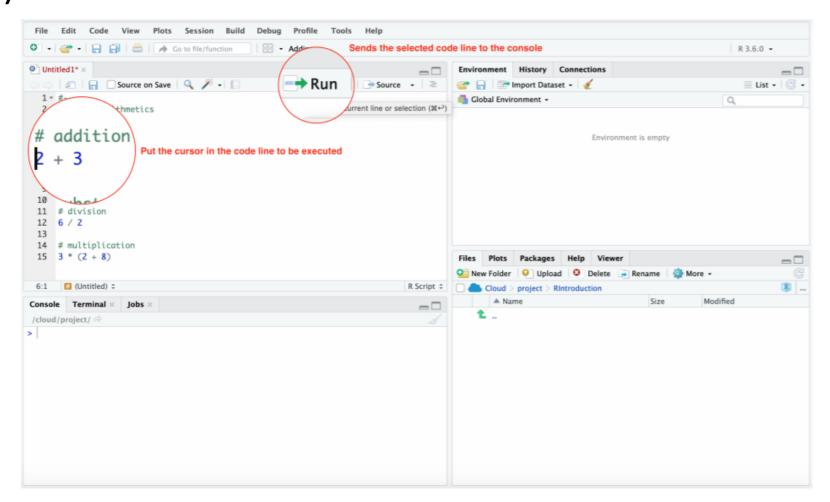


Script (.R) Paso 3: Escribimos el script





Script (.R) Paso 3: Corremos el script

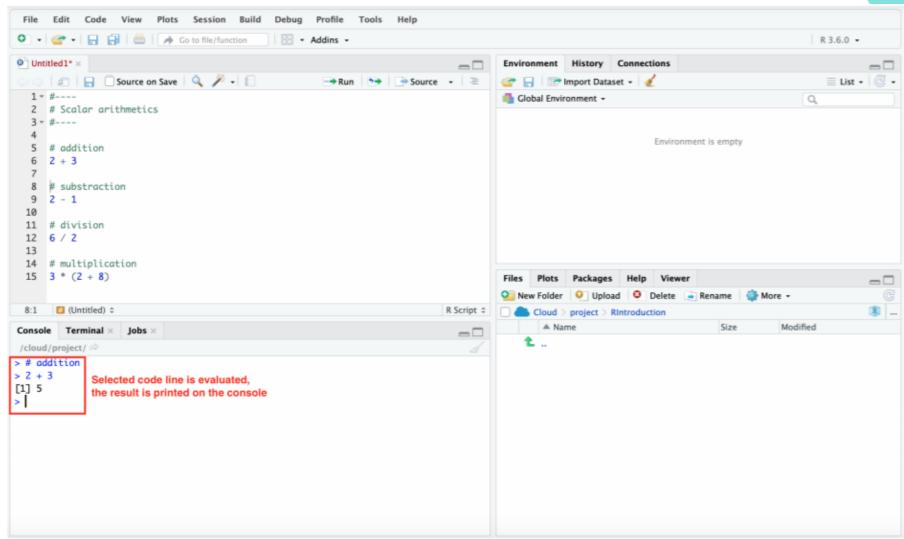




2. Qué nos ofrece software?

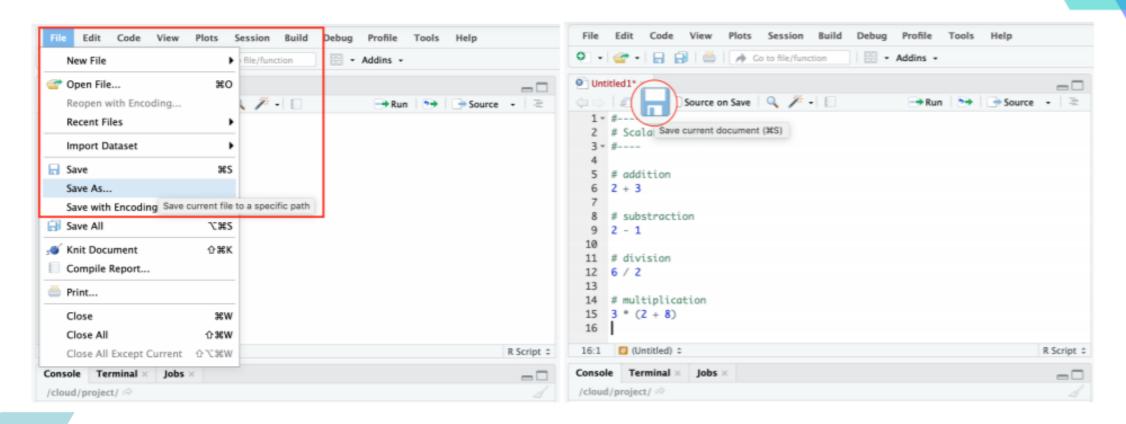
Script (.R)

Paso 3: Corremos el script



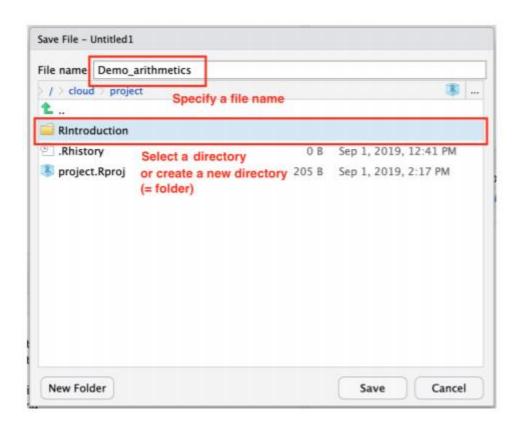


Script (.R) Paso 4: Guardamos el script



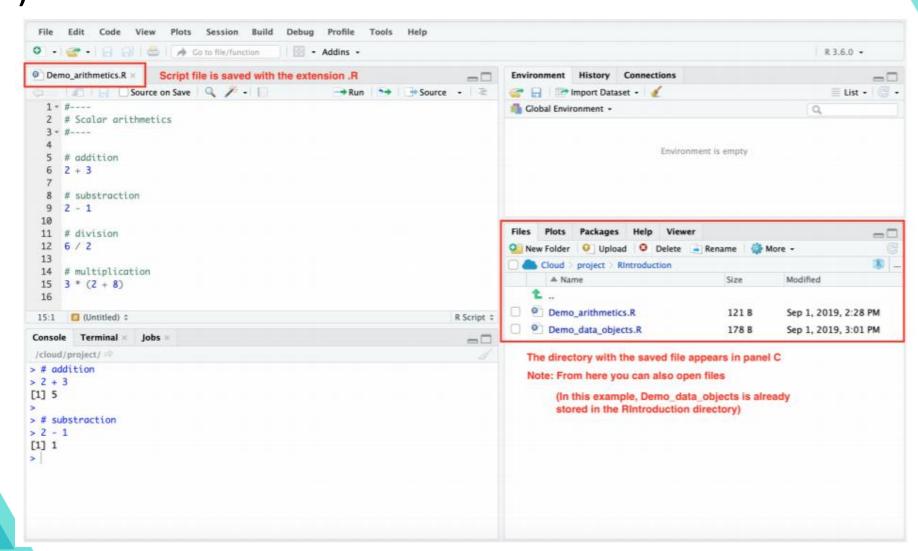


Script (.R) Paso 5: Guardamos el script



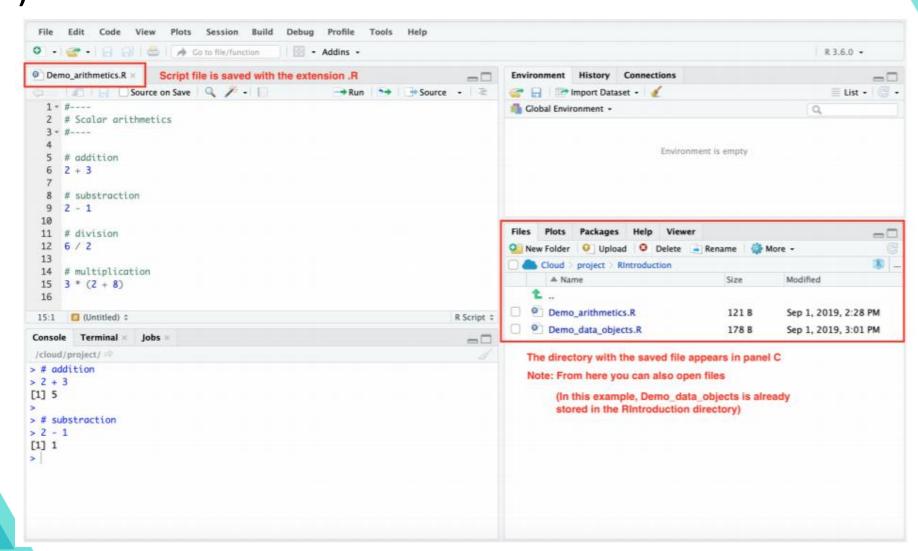


Script (.R) Paso 6: Guardamos el script





Script (.R) Paso 6: Guardamos el script





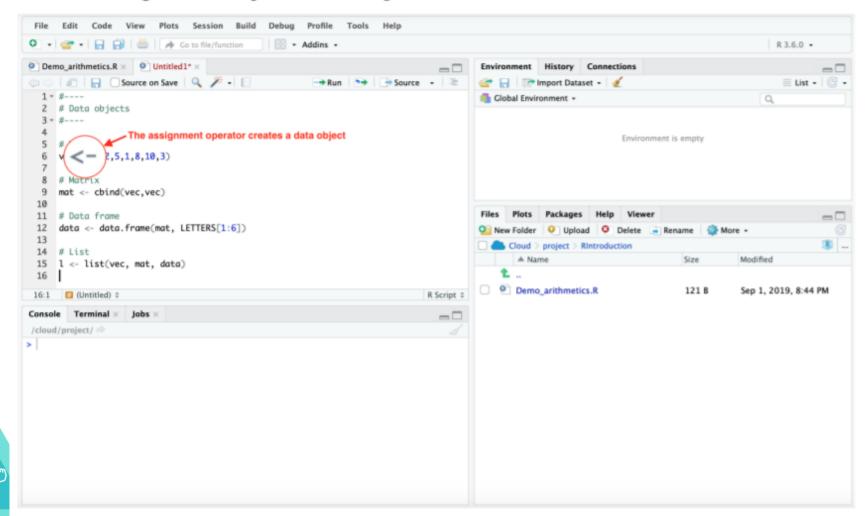
2.2. Shortcuts

	Windows (Linux)	Mac
New R Script file	Shift + Ctrl +N	Shift + CMD +N
Open file	Ctrl + O	Ctrl + 0
Run current line/selection and jump to next line	Ctrl + Enter	CMD + Enter
Run current line/selection DONT jump to next line	Alt + Enter	Alt + Enter
Run whole script	Ctrl + Alt + R	CMD + Alt + R
Run code from beginning to the current line	Ctrl + Alt + B	CMD + Alt + B
Run code from current line to end	Ctrl + Alt + E	CMD + Alt + E
Save current file	Ctrl + S	CMD + S
Close file	Ctrl + W	Ctrl + W
Move cursor to source editor	Ctrl + 1	Ctrl +1
Move cursor to console	Ctrl + 2	Ctrl + 2
Delete current selection	Ctrl + D	CMD + D
Clear console	Ctrl + L	Ctrl + L
Navigate console history	Up/Down	Up/Down
Move code line up and down (avoids copy-paste wor	k) Alt + Up/Down	Alt + Up/Down
Interrupt currently executing command	Esc	Esc

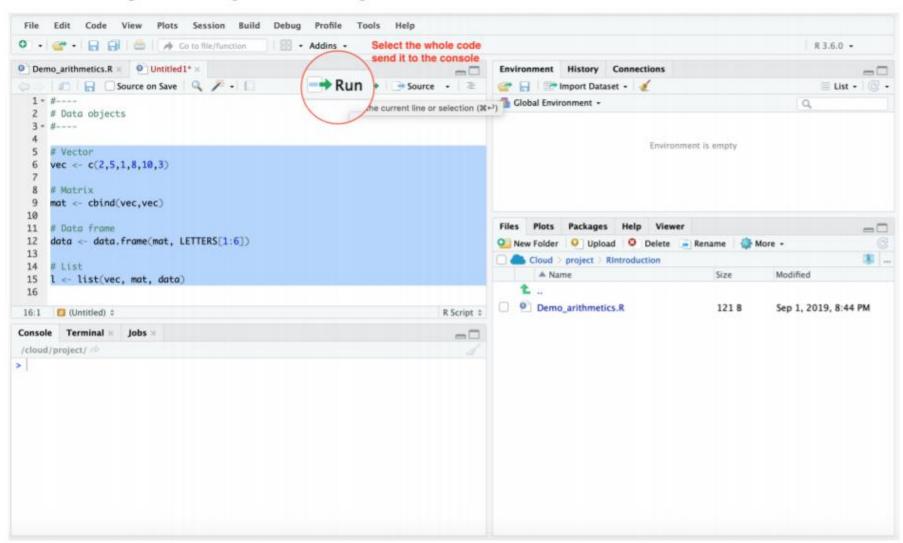


El workspace de R consiste en todos los objetos creados o cargados durante la sesión de R. Para crear objetos vamos a pegar y copiar el contenido de Demo_data_objects.txt en un nuevo script.

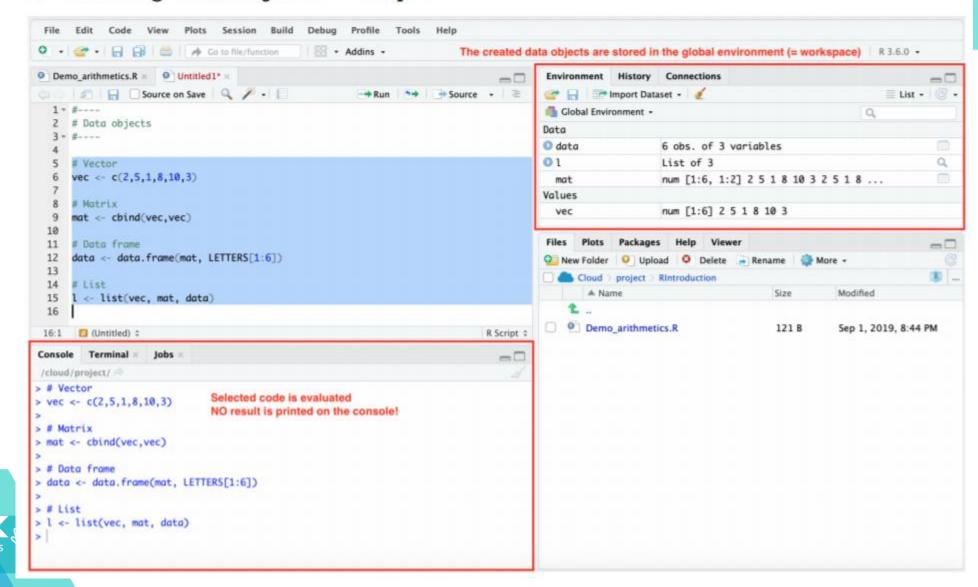
Creating data objects - Step 1



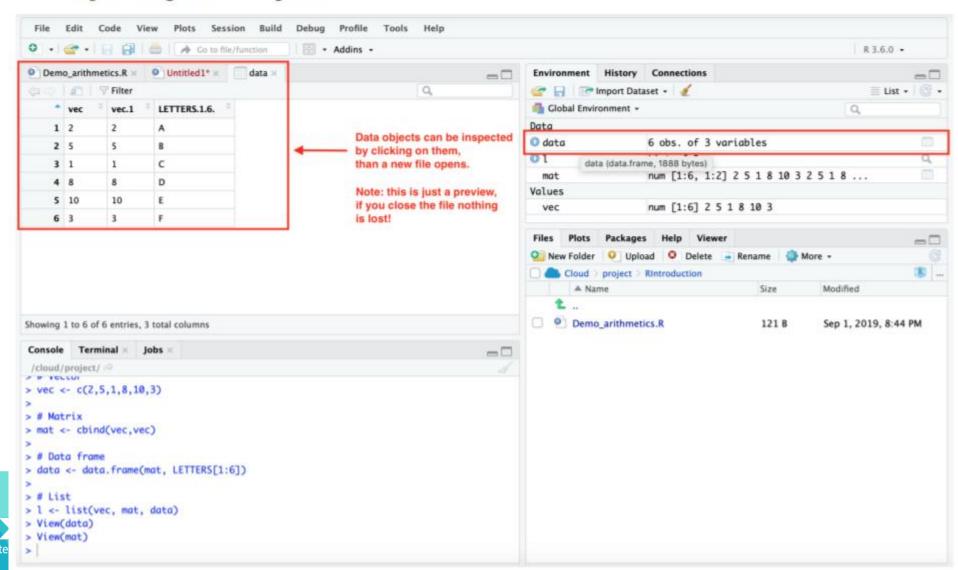
Creating data objects - Step 2



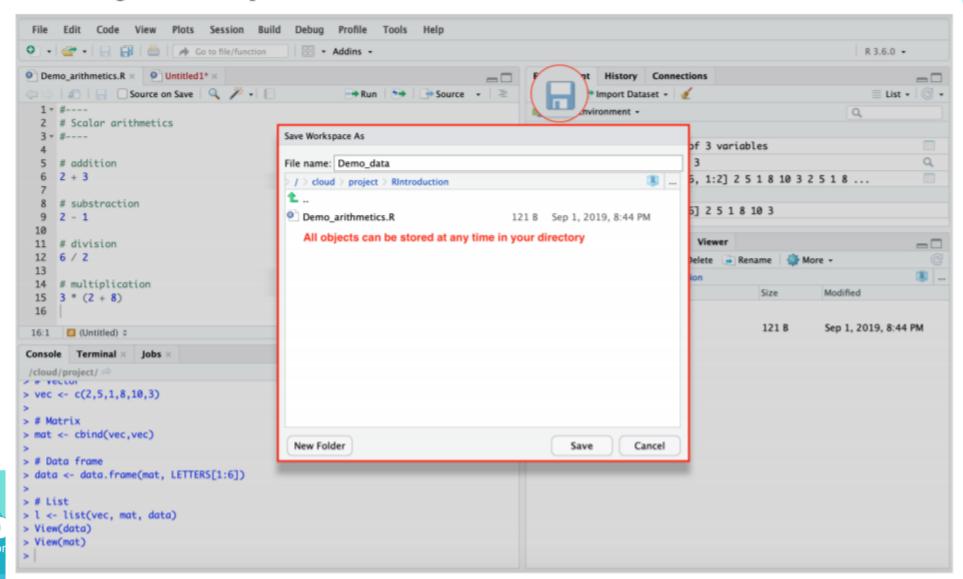
Creating data objects - Step 3



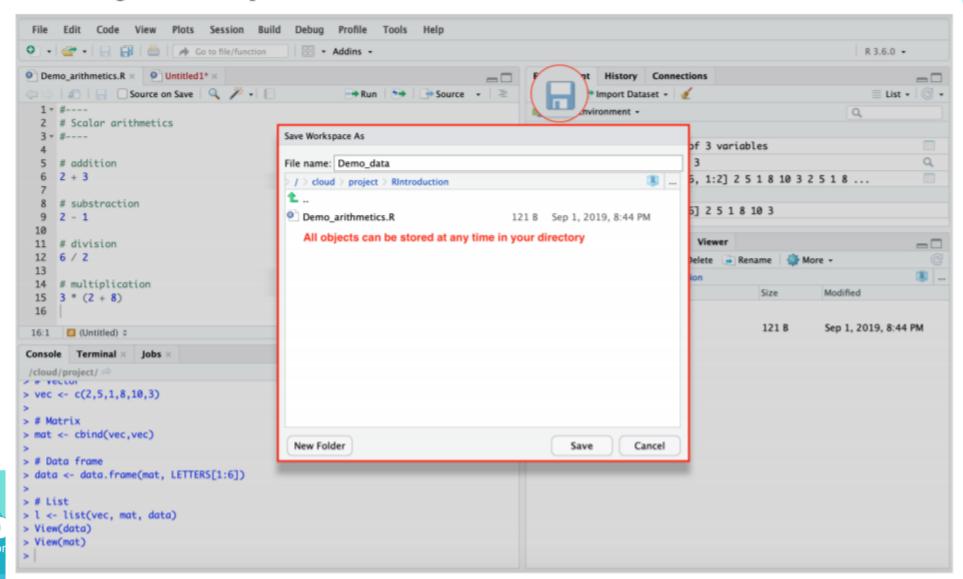
Inspecting data objects



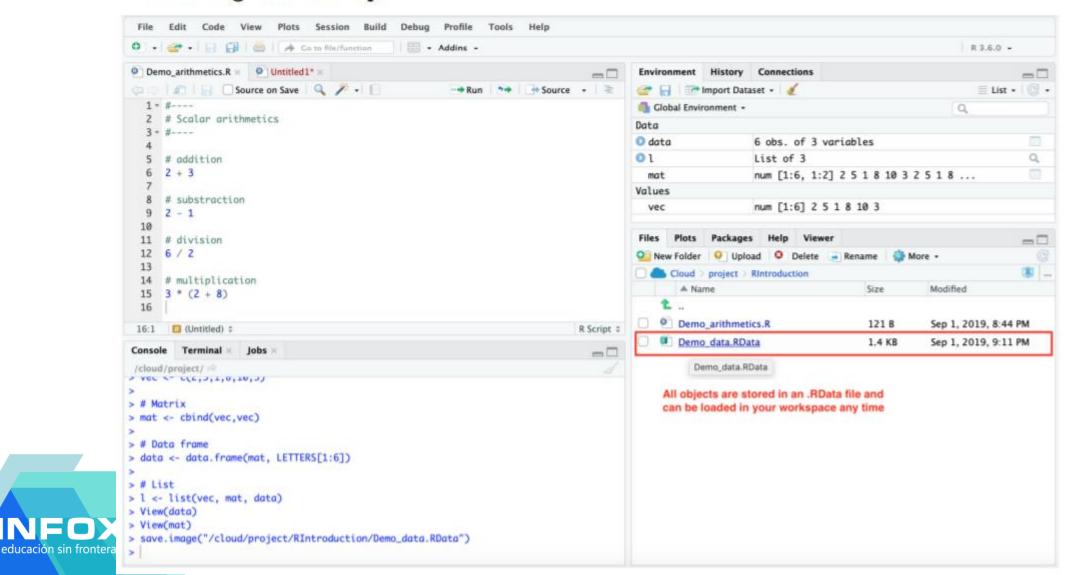
Saving the workspace



Saving the workspace

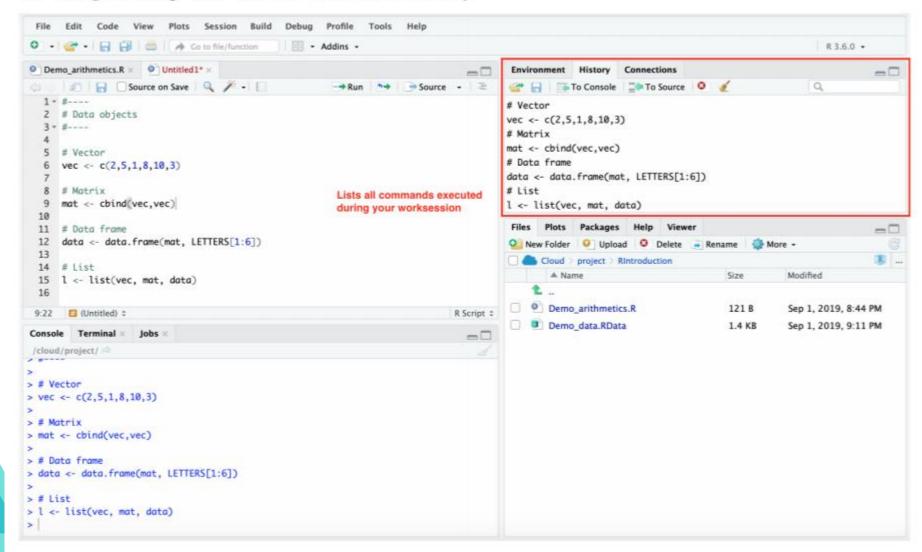


Loading the workspace



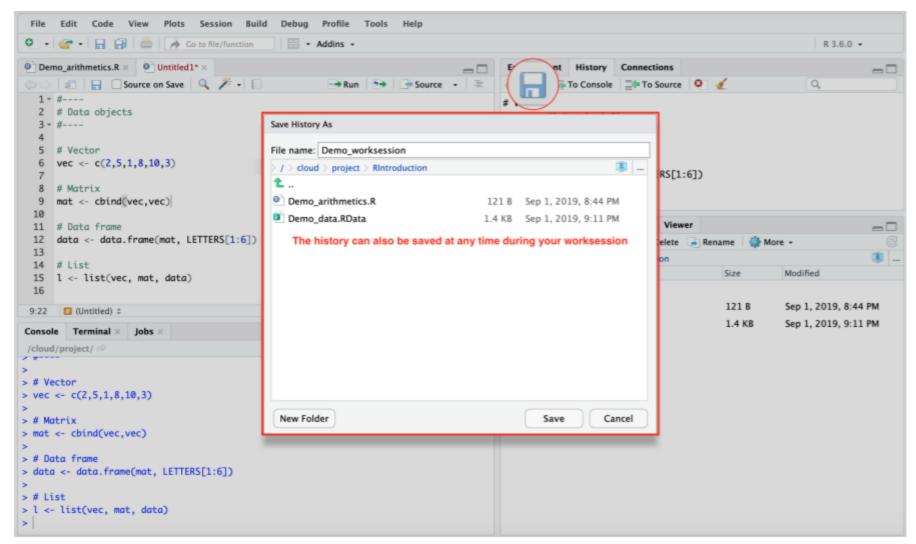
El History file es un text file que lista todos los comandos que se han ido ejecutando durante la sesión.

Inspecting the worksession history



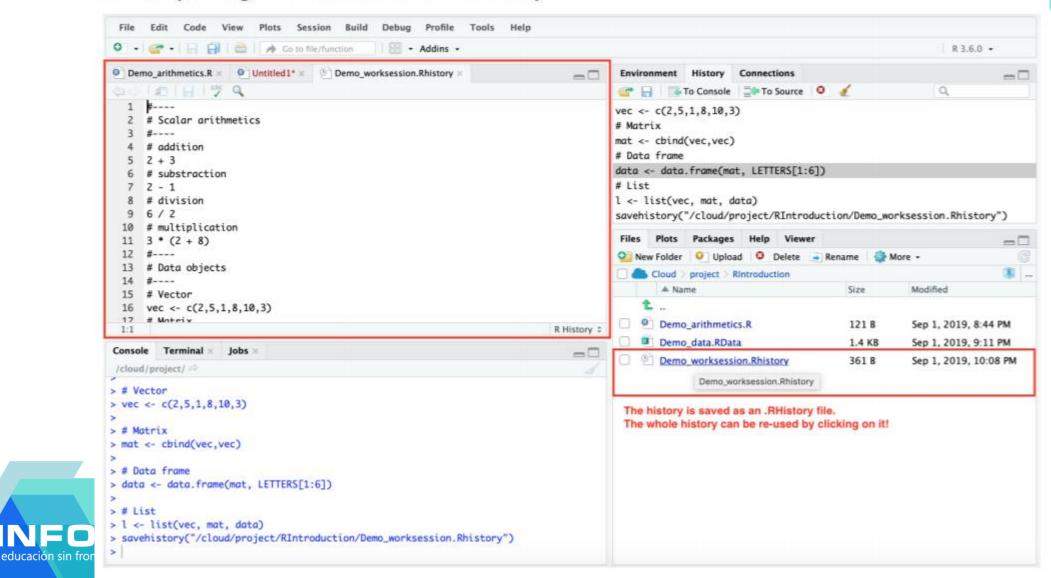


Saving the worksession history

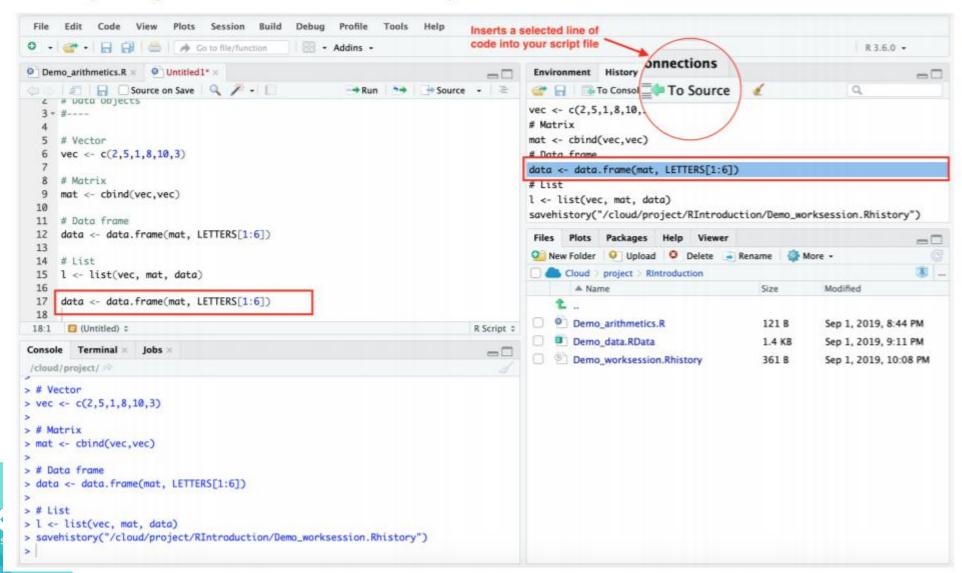




Recycling the worksession history



Recycling the worksession history





Agenda

3. Lo que debemos saber



3. Lo que debemos saber

Tipos de datos

En R tenemos 3 básicos tipos de datos:

- 1. a. Numérico (números reales)
- Los dos tipos de data más comunes son 'double' e 'integer'
 - b. Complejo (números imaginarios y reales)
- Lógico (boolean)Lógicas como TRUE y FALSE
- 3. Carácter

Es un tipo de data para almacenar letras y símbolos (strings, text)



3. Lo que debemos saber

Estructura de datos

- 1. Scalar
- 2. Vector: Collection of elements of a single ("atomic") data type
- 3. Matrix: Collection of elements arranged in a two-dimensional rectangular layout (a twodimensional generalization of a vector). Same as vector, all elements must be of a single data type.
- 4. Data frame: More general matrix like structure ("data matrix"). Different columns can have different data types.
- 5. List: Generic vector containing other objects. No restriction on data types or length of the single components



3. Lo que debemos saber

Estructura de datos

Vectors

Concatinating elements together with c().

```
> c(0.5, 0.6, 0.25)  # double
> c(9L, 10L, 11L, 12L, 13L)  # integer
> c(9:13)  # integer sequence
> c(TRUE, FALSE, FALSE)  # logical
> c(1+0i, 2+4i)  # complex
> c("a", "b", "c")  # character
```



Assign the vectors to names:

```
> dbl <- c(0.5, 0.6, 0.25)
> chr <- c("a", "b", "c")
```

Print out the dbl and chr vectors on the console:

> dbl

```
[1] 0.50 0.60 0.25
```

> chr

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

Check the number of elements in dbl and chr:

> length(dbl)

[1] 3

> length(chr)

[1] 3

Check the data type dbl and chr:

> typeof(dbl)

[1] "double"

> typeof(chr)

[1] "character"

Combine two vectors:

> c(dbl,dbl)

[1] 0.50 0.60 0.25 0.50 0.60 0.25

> c(dbl, chr)

[1] "0.5" "0.6" "0.25" "a" "b" "c

I The automatic change of the data type of the resulting vector is called **coercion**. Coercion ensures the same data type for each element in the vector is maintained.

Vector arithmetic

Define two new numeric vectors a and b each having 4 elements:

Multiply each element in a by 5 (scalar multiplication):

[1] 5 10 15 20

Multiply the elements in a by the elements in b (vector multiplication):

[1] 10 40 90 160

Multiply the elements in a by the elements of some numeric vector v of length 5:

Warning in a * v: Länge des längeren Objektes ist kein Vielfaches der Länge des kürzeren Objektes

[1] 1.1 2.4 3.9 5.6 1.5

Arithmetic operations of vectors are performed **elementwise**. If two vectors are of unequal length, the shorter vector will be **recycled** in order to match the longer one (here, the first element in a is used again).



Matrices

```
Option (1): Combining two vectors columnwise with cbind():
> A <- cbind(a, b) # two columns
> A
     a b
[1,] 1 10
[2,] 2 20
[3,] 3 30
[4,] 4 40
Option (2): Combining two vectors rowwise with rbind():
> B <- rbind(a, b) # two rows
> B
```

Option (3): Creating a matrix from elements of a vector with matrix():

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



The arguments nrow and ncol indicate the number of rows and number of columns the resulting matrix consists of.

For 4 elements and ncol = 2 the matrix can only have 2 rows. Thus, there is no need to specify both arguments.

```
> A <- matrix(a, ncol=2)  # matrix with 2 columns and 2 rows
> A
```

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

By default the matrix is filled up column after column (R treats a matrix object internally as a column vector). If the matrix should be filled up row after row the argument byrow= TRUE is required.

```
> B <- matrix(a, ncol=2, byrow=TRUE) # matrix filled-up rowwise
> B
```

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



Matrix actions

Checking the number of rows:

> nrow(B)

[1] 2

Checking the number of columns:

> ncol(B)

[1] 2

Checking the dimension [nrow, ncol]:

> dim(B)

[1] 2 2

Combine two matrices:

> D.wide <- cbind(A,A)

> D.wide

> D.long <- rbind(A,A)

> D.long



Matrix addition:

> B + B

	[,1]	[,2]
[1,]	2	4
[2,]	6	8

Scalar multiplication:

> B * 2

Elementwise multiplication:

> B * B

Matrix multiplication:

> B %*% B

More matrix arithmetic

- Transpose t()
- > D.wide

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

> t(D.wide)

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

- Determinant det()
- > det(B)

[1] -2

- Inverse solve() (only if det() ≠ 0)
- > solve(B)

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

Eigenvalues eigen() (only for square and symmetric matrices)



3. Lo que debemos saber Dataframes

```
> dbl <- c(0.5, 0.6, 0.25, 1.2, 0.333)
                                          # double
> int <- c(9L, 10L, 11L, 12L, 13L)
                                          # integer
> lgl <- c(TRUE, FALSE, FALSE, TRUE, TRUE)
                                          # logical
> chr <- c("a", "b", "c", "d", "e")
                                          # character
> df <- data.frame(dbl,int,lgl,chr)</pre>
> df
   dbl int lgl chr
1 0.500 9 TRUE a
2 0.600 10 FALSE b
3 0.250 11 FALSE c
4 1.200 12 TRUE d
5 0.333 13 TRUE e
```

Data frame actions

Checking the number of rows:

```
> nrow(df)
```

[1] 5

Checking the number of columns:

> ncol(df)

[1] 4

Checking the dimension [nrow, ncol]:

> dim(df)

[1] 5 4



3. Lo que debemos saber Lists

```
> a <- 1L
                                              # scalar
> dbl <- c(0.5, 0.6, 0.25, 1.2, 0.333)
                                              # numeric vector of length 5
> chr <- c("a", "b", "c" )
                                              # charcter vector of length 3
> v <- c(1.1, 1.2, 1.3, 1.4)
> mat <- matrix(v, ncol=2)</pre>
                                              # 2 x 2 matrix
> 1 <- list(a, dbl, chr, mat)
> 1
[[1]]
[1] 1
[[2]]
[1] 0.500 0.600 0.250 1.200 0.333
[[3]]
[1] "a" "b" "c"
[[4]]
   [,1] [,2]
[1,] 1.1 1.3
[2,] 1.2 1.4
```

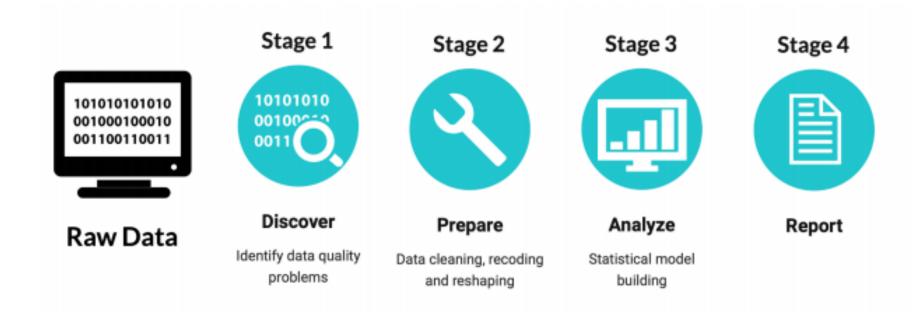


Agenda

4. Manipulación de datos



The data science process





Discover

- Real-world data is generally noisy, incomplete and inconsistent. The initial exploration of the raw data set helps you to spot such data quality problems.
- Scanning your data also helps you to discover first insights into it and provides guidance on applying the right kind of further statistical treatment to it.

Prepare and Analyse

- Analytical models fed with poor quality data can lead to misleading predictions. The data
 preparation stage resolves data issues and ensures the dataset used in the modeling stage is
 acceptable and of improved quality.
- Data preparation tasks are likely to be performed multiple times during interactive data analysis and model building stages (also called data wrangling or data munging). That's why data prepartion typically consumes around 80% of overall time of an analytics project.



Stage 1: Discover

Data inspection constitutes a set of simple tools to answer questions like:

Question 1: What is the size the data set?

Question 2: What variables are included?

Question 3: Are there implausible/ missing values?

Question 4: How are values distributed over variables?



Ejemplo: Dataset BenandJerry ice cream- Subsample of the Nielson homescan data, a consumer panel consisting of 70, 000 households and all their purchases.

Question 1: What is the size of the data set?

Check the number of columns and rows (or alternatively the dimension) of the data set:

> nrow(BenAndJerry)

[1] 21974

> ncol(BenAndJerry)

[1] 12

> dim(BenAndJerry)

[1] 21974 12

Question 2: What variables are included?

Check the column names:

> names(BenAndJerry)

```
[1] "quantity" "price_paid_deal" "price_paid_non_deal"
[4] "coupon_value" "promotion_type" "total_spent"
[7] "size1_descr" "flavor_descr" "formula_descr"
[10] "household_id" "female_head_birth" "male_head_birth"
```

Display the first observations:

> head(BenAndJerry)

Display the last observations:

> tail(BenAndJerry)



Display the structure of the data set:

> str(BenAndJerry)

```
Classes 'tbl df', 'tbl' and 'data.frame': 21974 obs. of 12 variables:
 $ quantity
                     : int 2 1 1 1 1 2 2 1 1 1 ...
 $ price paid deal : num 6.82 3.5 3.5 0 0 0 0 2.14 3.5 3 ...
 $ price paid non deal: num
                           0 0 0 3 3.99 7.78 7.78 0 0 0 ...
 $ coupon value
                    : num 1 0 0 0 0 0 0 0 1.25 ...
 $ promotion type
                    : int 2 1 1 NA NA NA NA 1 1 2 ...
 $ total spent
                           37.2 31 15.5 113 67.3 ...
                   : num
 $ size1_descr
                           "16.0 MLOZ" "16.0 MLOZ" "16.0 MLOZ" "16.0 M"...
                     : chr
 $ flavor descr
                           "CAKE BATTER" "VAN CARAMEL FUDGE" "VAN CARA"...
                     : chr
 $ formula descr
                           "REGULAR" "REGULAR" "REGULAR" ...
                     : chr
 $ household id
                           2001456 2001456 2001456 2001637 2002791 2002...
                     : int
 $ female head birth : chr NA NA NA "10/1/36" ...
 $ male head birth
                     : chr "10/1/61" "10/1/61" "10/1/61" NA ...
```

Here: one line for each column in the data set (including its name, data type and the first few observations) is displayed.

The str()-function gives a reasonable output for any R object by compactly displaying its content. It is particularly well-suited for **list** objects. Recap: a list is a generic vector containing other objects.



Technically, R considers a **data frame** internally as a list object. Thus, a data frame is a **list of equal-length vectors**. Therefore, the length() of a data frame is the length of the underlying list and gives the same result as ncol(); whereas nrow() gives the number of rows.

> length(BenAndJerry)

[1] 12

> ncol(BenAndJerry)

[1] 12

> nrow(BenAndJerry)

[1] 21974

- Use \$ to extract columns by their name!
- > head(BenAndJerry\$price_paid_deal)

[1] 6.82 3.50 3.50 0.00 0.00 0.00



Question 3: Are there implausible/ missing values?

Check for observations with 0 or negative pruchases:

> BenAndJerry\$total_spent <= 0

[1] FALSE FALSE FALSE FALSE FALSE

Here: the result is of type logical.

Internally, R treats TRUE and FALSE as 0 and 1 values. Thus, we can sum over all TRUE and FALSE values and do not need to check each single value:

> sum(BenAndJerry\$total_spent <= 0)

[1] 0

⇒ There are no observations with 0 or negative purchases.

More logical operators

- larger than: >; less than: <
- larger than or equal to: >=; less than or equal to: <=
- exactly equal to: ==; not equal to: !=
- negotiation of x: !x
- all x values larger than 0 AND smaller than 1: (x > 0) & (x < 1)
- any x value larger than 0 OR smaller than 1: (x > 0) | (x < 1)

- Check for observations with missing purchases (missings are coded with NA):
- > is.na(BenAndJerry\$total_spent)
- [1] FALSE FALSE FALSE FALSE FALSE
- > sum(is.na(BenAndJerry\$total_spent))
- [1] 0
- ⇒ There are no missing values for purchases.



Question 4: How are values distributed over variables?

Calculate the average price paid for deal and non deal:

> mean(BenAndJerry\$price_paid_deal)

[1] 1.74206

> mean(BenAndJerry\$price_paid_non_deal)

[1] 2.452375

Calculate the spread of the values:

> var(BenAndJerry\$price_paid_deal)

[1] 6.519148

> sqrt(var(BenAndJerry\$price_paid_deal))

[1] 2.553262

> sd(BenAndJerry\$price_paid_deal)

[1] 2.553262

More statistic functions

- min() / max() (minimum, maximum value)
- range() (max() min())
- median()
- mode()





Stage 2: Prepare

Data preparation covers all activities used to construct the final dataset from the initial raw data

- Creating new data objects (transform or recode values)
- Excluding implausible values (subset)
- Constructing new data sets (aggregate over observations, reshape the data set)

Example: Ben&Jerry ice-cream (continued).

Calculate the price_paid_deal and price_paid_non_deal <u>per unit</u>. Create two new data objects Unit.price.deal and Unit.price.non.deal:

- > Unit.price.deal <- BenAndJerry\$price_paid_deal/BenAndJerry\$quantity
- > Unit.price.non.deal <- BenAndJerry\$price_paid_non_deal/BenAndJerry\$quantity

Calculate the average unit price paid for deal and non deal:

> mean(Unit.price.deal)

[1] 1.328127

- > mean(Unit.price.non.deal)
- [1] 1.986501



The newly created unit price data vectors can also be appended to the data matrix by using \$:

- > BenAndJerry\$Unit.price.deal <- Unit.price.deal
- > BenAndJerry\$Unit.price.non.deal <- Unit.price.non.deal
- > names(BenAndJerry)

```
[1] "quantity" "price_paid_deal" "price_paid_non_deal"
[4] "coupon_value" "promotion_type" "total_spent"
[7] "size1_descr" "flavor_descr" "formula_descr"
[10] "household_id" "female_head_birth" "male_head_birth"
[13] "Unit.price.deal" "Unit.price.non.deal"
```

⇒ The unit price data vectors are added on the last position (the last two columns).



It might be useful to also examine Unit.price.deal and Unit.price.non.deal in combination with other attributes like size1_descr (package size), formula_descr (fat) and flavor_descr (flavor). This can be done by using the aggregate()-function:

```
aggregate(formula, data, FUN, subset, na.action = na.omit, ...)
```

- formula: A formula argument where the response variables are numeric data, to be split into groups according to the values in the predictor variables.
- data: data frame or list.
- <u>FUN</u>: function to compute the summary statistics, for example, mean() or var().
- <u>subset</u>: specify a subset of the observations to be analysed (see also subset()).
- na.action: what should happen with observations containing NA (missing) values? (ignored by default)



- In R, formulas are used to express a relationship between variables. Most commonly, the relationship between one **response** and one (or several) **predictor** variable(s) is described.
 - The formula is characterized by the tilde ~ symbol. The response variable stands on the **left** hand side and the **predictor** variable on the **right** hand side of the tilde:

```
response ~ predictor
```

Predictor variables can be added with the plus + symbol:

```
response ~ predictor1 + predictor2
```

More formulas

leave out predictor2:

```
response ~ predictor1 - predictor2
```

tensor product (interactions) of predictor1 and predictor2:

```
response ~ predictor1 : predictor2
```

crossing:

```
response ~ predictor1 * predictor2
same as
response ~ predictor1 + predictor2 + predictor1 : predictor2
```

In the following, we consider Unit.price.deal as the response variable and size1 descr as the predictor variable for specifying the formula argument in the aggregate()-function:

```
> aggregate(Unit.price.deal ~ size1 descr,
           <u>FUN = mean, data = BenAndJerry</u>)
  size1_descr Unit.price.deal
  16.0 MLOZ
                   1.3355396
   32.0 MLOZ
                   0.8940921
⇒ Groups the average Unit.price.deal according to the different package sizes.
> aggregate(Unit.price.deal ~ size1 descr + formula descr,
           <u>FUN = mean, data = BenAndJerry</u>)
> aggregate(Unit.price.deal ~ size1_descr * formula_descr,
            <u>FUN = mean, data = BenAndJerry</u>)
  size1 descr
                  formula descr Unit.price.deal
   16.0 MLOZ LIGHT HALF THE FAT
                                       1.7091622
  16.0 MLOZ
                         REGULAR 1.3290296
   32.0 MLOZ
                         REGULAR
                                       0.8940921
```



⇒ Groups the mean of Unit.price.deal according to package size crossed with amount of fat (factorial design).

⇒ Only observations with purchases larger than 0 are considered (i.e. purchases smaller than or equal to 0 are excluded).

```
      size1_descr
      formula_descr
      Unit.price.deal
      Unit.price.non.deal

      1
      16.0 MLOZ LIGHT HALF THE FAT
      1.7091622
      1.701405

      2
      16.0 MLOZ
      REGULAR
      1.3290296
      1.956975

      3
      32.0 MLOZ
      REGULAR
      0.8940921
      3.971491
```

⇒ Groups both the average Unit.price.deal and Unit.price.non.deal according package size and fat.



¡GRACIAS!

