Introduction to Spatial Data Programming - R

Lesson 04
Tables

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Contents

Aims

- Learn to work with `data.frame`, the data structure used to represent tables in R
- Learn several automation methods for controlling code execution and automation in R -
  - Conditionals
  - Loops
  - The `apply` function
- Install and use packages beyond "base R"
- Join between tables

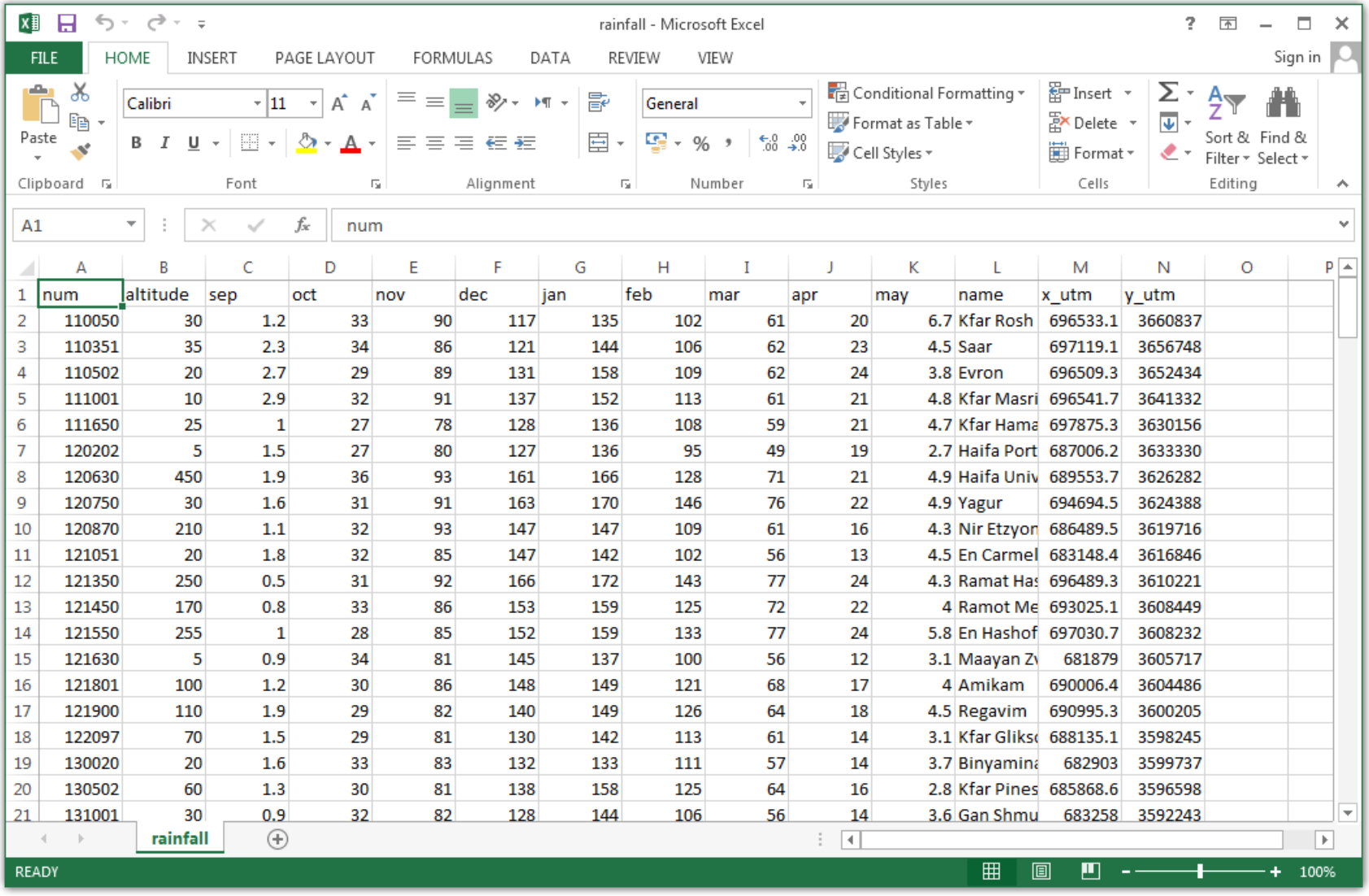
Preparation

```
library(dplyr)
```

Table

- A **table** in R is represented using the `data.frame` class
- A `data.frame` is basically a collection of **vectors** comprising columns, all of the **same size** but possibly of **different types**
- Conventionally -
  - Each row represents an **observation**, with values possibly of a **different** type for each variable
  - Each column represents a **variable**, with values of the **same** type

Table



num	altitude	sep	oct	nov	dec	jan	feb	mar	apr	may	name	x_utm	y_utm
110050	30	1.2	33	90	117	135	102	61	20	6.7	Kfar Rosh	696533.1	3660837
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Figure 1: `rainfall.csv` opened in Excel

Creating a data.frame

- A data.frame can be **created** with the data.frame function, given one or more vectors which become columns
- The stringAsFactors=FALSE argument *prevents* the conversion of **text columns** to factor, which is what we usually want

```
d = data.frame(
  num = c(3, 7, 1),
  word = c("three", "seven", "one"),
  stringsAsFactors = FALSE
)
d
##   num  word
## 1   3 three
## 2   7 seven
## 3   1   one
```

Interactive view of a `data.frame`

- The `View` function opens an **interactive view** of a `data.frame`
- When using RStudio, the view also has **sort** and **filter** buttons
- Note: sorting or filtering the view have no effect on the object

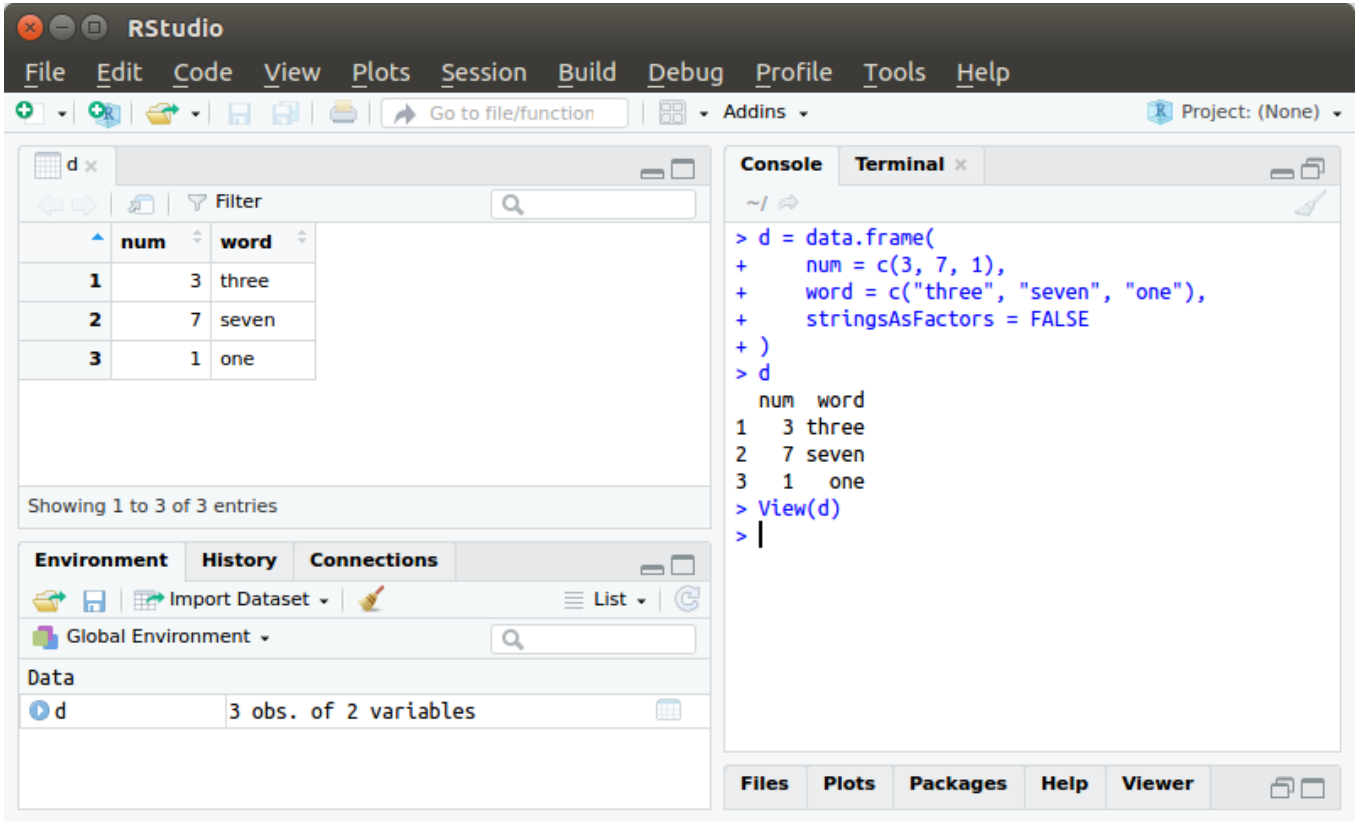

Figure 2: Table view in Rstudio

data.frame properties

- We can get the number of **rows** and number of **columns** in a `data.frame` with `nrow` and `ncol`, respectively -

```
nrow(d)
## [1] 3
```

```
ncol(d)
## [1] 2
```

- Or **both** of them as a vector of length 2 with `dim` -

```
dim(d)
## [1] 3 2
```

data.frame properties

- data.frames have row and column **names**, which we can get with rownames and colnames, respectively -

```
rownames(d)
## [1] "1" "2" "3"
```

```
colnames(d)
## [1] "num"  "word"
```

data.frame properties

- We can also **set** row or column names by assigning new values to these properties -

```
colnames(d)[1] = "Number"
d
##   Number  word
## 1      3 three
## 2      7 seven
## 3      1   one
```

```
colnames(d)[1] = "num"
d
##   num  word
## 1   3 three
## 2   7 seven
## 3   1   one
```

data.frame properties

- `str` gives a summary of the object **structure** -

```
str(d)
## 'data.frame':    3 obs. of  2 variables:
##  $ num : num  3 7 1
##  $ word: chr  "three" "seven" "one"
```

`data.frame` subsetting

- A `data.frame` **subset** can be obtained with the `[` operator
- A `data.frame` is a two-dimensional object, therefore the index is composed of **two vectors** -
  - The first vector refers to **rows**
  - The second vector refers to **columns**
- Each of these vectors can be one of the following **types** -
  - `numeric` - Specifying the **indices** of rows/columns to retain
  - `character` - Specifying the **names** of rows/columns to retain
  - `logical` - Specifying **whether** to retain each row/column
- The rows or column index can be **omitted**, in which case we get all rows or all columns, respectively

data.frame subsetting

```
d[1, 1]          # Row 1, column 1
## [1] 3

d[c(1, 3), 2]    # Rows 1 & 3, column 2
## [1] "three" "one"

d[2, ]           # Row 2
##   num  word
## 2   7 seven

d[, 2:1]         # Columns 2 & 1
##    word num
## 1 three   3
## 2 seven   7
## 3   one   1
```

data.frame subsetting

- A subset with a **single column** can be returned as -
  - A vector (`drop=TRUE`, the default)
  - A `data.frame` (`drop=FALSE`)
- For example -

```
d[1:2, 1]
## [1] 3 7
```

```
d[1:2, 1, drop = FALSE]
##   num
## 1   3
## 2   7
```

- Question: why do you think this applies to a single column, rather than a single row?

data.frame subsetting

- We can also use a `character` index to specify the **names** of rows and/or columns to retain in the subset -

```
d[, "num"]
## [1] 3 7 1
```

- The `$` operator is a shortcut for getting a **single column** from a `data.frame` -

```
d$num
## [1] 3 7 1
```

```
d$word
## [1] "three" "seven" "one"
```

Subset operators in R

Table 1: Subset operators in R

Syntax	Objects	Returns
`x[i]`	**vector**, **table**, **matrix**, **array**, **list**	Subset `i`
`x[[i]]`	vectors, **lists**	Single element `i`
`x$i`	**tables**, lists	Single element `i`
`x@n`	S4 objects	Slot `n`

data.frame subsetting

- The third option for a `data.frame` index is a `logical` vector, specifying **whether** to retain each row or column
- Most commonly it is used to filter `data.frame` **rows** based on the values of one or more **columns** -

```
d[d$num == 1, ]
##   num word
## 3   1  one
```

```
d[d$word == "seven" | d$word == "three", ]
##   num  word
## 1   3 three
## 2   7 seven
```

data.frame subsetting

- Let's go back to the Kinneret example from **Lesson 03** -

```
may = c(
  -211.92,-208.80,-208.84,-209.12,-209.01,-209.60,
  -210.24,-210.46,-211.76,-211.92,-213.13,-213.18,
  -209.74,-208.92,-209.73,-210.68,-211.10,-212.18,
  -213.26,-212.65,-212.37
)
nov = c(
  -212.79,-209.52,-209.72,-210.94,-210.85,-211.40,
  -212.01,-212.25,-213.00,-213.71,-214.78,-214.34,
  -210.93,-210.69,-211.64,-212.03,-212.60,-214.23,
  -214.33,-213.89,-213.68
)
```

data.frame subsetting

- Using these vectors we will construct the following `data.frame` -

```
kineret = data.frame(year = 1991:2011, may, nov)
```

```
head(kineret)
##   year     may     nov
## 1 1991 -211.92 -212.79
## 2 1992 -208.80 -209.52
## 3 1993 -208.84 -209.72
## 4 1994 -209.12 -210.94
## 5 1995 -209.01 -210.85
## 6 1996 -209.60 -211.40
```

data.frame subsetting

- Using a **logical index** we can get a subset of years when the Kinneret level in May was less than -213 -

```
kineret[kineret$may < -213, "year"]   # Method 1
## [1] 2001 2002 2009
```

```
kineret$year[kineret$may < -213]      # Method 2
## [1] 2001 2002 2009
```

- Similarly, we can get a subset with **all data** for those years -

```
kineret[kineret$may < -213, ]
##    year     may     nov
## 11 2001 -213.13 -214.78
## 12 2002 -213.18 -214.34
## 19 2009 -213.26 -214.33
```

Creating new columns

- Assignment into a column which does not exist adds a **new column** -

```
kineret$d_nov = c(NA, diff(kineret$nov))
```

```
head(kineret)
##   year      may      nov d_nov
## 1 1991 -211.92 -212.79    NA
## 2 1992 -208.80 -209.52  3.27
## 3 1993 -208.84 -209.72 -0.20
## 4 1994 -209.12 -210.94 -1.22
## 5 1995 -209.01 -210.85  0.09
## 6 1996 -209.60 -211.40 -0.55
```

Flow control

- The default is to let the computer execute **all** expressions in the same **order** they are given in the code
- Flow control commands are a way to **modify** the sequence of code execution
- We learn two flow control operators, from two categories -
  - `if` and `else` - A **conditional**, conditioning the execution of code
  - `for` - A **loop**, executing code more than once

Conditionals

- The purpose of the **conditional** is to condition the execution of code
- An `if-else` conditional in R contains the following components -
  - The `if` keyword
  - A condition
  - Code to be executed if the condition is `TRUE`
  - The `else` keyword (optional)
  - Code to be executed if the condition is `FALSE` (optional)
- The condition needs to be evaluated to a **single logical value** (`TRUE` or `FALSE`); If it is `TRUE` then the code section after `if` is executed

Conditionals

- Conditional with `if` -

```
if(condition) {
  expressions
}
```

- Conditional with `if` and `else` -

```
if(condition) {
  trueExpressions
} else {
  falseExpressions
}
```

Conditionals

- For example -

```
x = 3
x > 2
## [1] TRUE

if(x > 2) print("x is large!")
## [1] "x is large!"
```

```
x = 0
x > 2
## [1] FALSE

if(x > 2) print("x is large!")
```

Conditionals

- Now also with `else`
- The first code section is executed when the condition is `TRUE` -

```
x = 3
if(x > 2) print("x is large!") else print("x is small!")
## [1] "x is large!"
```

- The second code section is executed when the condition is `FALSE` -

```
x = 1
if(x > 2) print("x is large!") else print("x is small!")
## [1] "x is small!"
```

Conditionals

- We can use a conditional to write our own version of the `abs` function -

```
abs2 = function(x) {
  if(x >= 0) return(x) else return(-x)
}
```

- For example -

```
abs2(-3)
## [1] 3
```

```
abs2(24)
## [1] 24
```

Conditionals

- Question 1: what happens when the argument of `abs2` is of length >1?
- Question 2: write a function `is_myname` that checks if the given text is your name, returning `TRUE` or `FALSE`

```
is_myname("Michael")
## [1] TRUE
is_myname("Yossi")
## [1] FALSE
```

Loops

- A **loop** is used to execute a given code section more than once
- The number of **times** the code is executed is determined in different ways in different types of loops
- In a `for` loop, the number of times the code is executed is determined in advance based on the length of a **vector** passed to the loop
- The code is executed once for **each element** of the vector
- In each "round", the current element is assigned to a **variable** which we can use in the loop code

Loops

- A `for` loop is composed of the following parts -
  - The `for` keyword
  - The variable name `symbol` getting the current vector value
  - The `in` keyword
  - The vector `sequence`
  - A code section `expressions`

```
for(symbol in sequence) {
  expressions
}
```

- Note: the constant keywords are just `for` and `in`

Loops

- For example -

```
for(i in 1:5) print(i)
## [1] 1
## [1] 2
## [1] 3
## [1] 4
## [1] 5
```

- The expression `print(i)` is executed 5 times, according to the length of the vector `1:5`
- Each time, `i` gets the next value of `1:5` and the code section prints `i` on screen

Loops

- The vector defining the `for` loop does not necessarily need to be numeric -

```
for(b in c("Test", "One", "Two")) print(b)
## [1] "Test"
## [1] "One"
## [1] "Two"
```

- The expression `print(b)` is executed 3 times, according to the length of the vector `c("Test", "One", "Two")`
- Each time, `b` gets the next value of the vector and the code section prints `b` on screen

Loops

- In case the vector is numeric, it does not necessarily need to be composed of consecutive -

```
for(i in c(1,15,3)) print(i)
## [1] 1
## [1] 15
## [1] 3
```

- The expression `print(i)` is executed 3 times, according to the length of the vector `c(1,15,3)`
- Each time, `i` gets the next value of the vector and the code section prints `i` on screen

Loops

- The code section does not have to use the current value of the vector -

```
for(i in 1:5) print("A")
## [1] "A"
## [1] "A"
## [1] "A"
## [1] "A"
## [1] "A"
```

- The expression `print("A")` is executed 5 times, according to the length of the vector `1:5`
- Each time, the code section prints `"A"` on screen

Loops

- The following `for` loop prints each of the numbers from 1 to 10 multiplied by 5 -

```
for(i in 1:10) print(i * 5)
## [1] 5
## [1] 10
## [1] 15
## [1] 20
## [1] 25
## [1] 30
## [1] 35
## [1] 40
## [1] 45
## [1] 50
```

Loops

- Question: How can we prints a multiplication table for 1-10, using a `for` loop?

```
##  [1]  1  2  3  4  5  6  7  8  9 10
##  [1]  2  4  6  8 10 12 14 16 18 20
##  [1]  3  6  9 12 15 18 21 24 27 30
##  [1]  4  8 12 16 20 24 28 32 36 40
##  [1]  5 10 15 20 25 30 35 40 45 50
##  [1]  6 12 18 24 30 36 42 48 54 60
##  [1]  7 14 21 28 35 42 49 56 63 70
##  [1]  8 16 24 32 40 48 56 64 72 80
##  [1]  9 18 27 36 45 54 63 72 81 90
##  [1]  10  20  30  40  50  60  70  80  90 100
```

Loops

- As another example of using a `for` loop, we can write a function named `x_in_y`
- The function accepts **two vectors** `x` and `y`
- For each **element** in `x` the function checks if it is **found** in `y`
- It returns a `logical` vector of the same length as `x`
- For example -

```
x_in_y(c(1, 2, 3, 4, 5), c(2, 1, 5))
## [1]  TRUE  TRUE FALSE FALSE  TRUE
```

Loops

- We can use a `for` **loop** to check if each element in `x` is contained in `y` -

```
x = c(1, 2, 3, 4, 5)
y = c(2, 1, 5)
```

```
for(i in x) print(any(i == y))
## [1] TRUE
## [1] TRUE
## [1] FALSE
## [1] FALSE
## [1] TRUE
```

Loops

- In a function, we can **"collect"** the results into a vector instead of printing them on screen -

```
# Version 1
x_in_y = function(x, y) {
  result = NULL
  for(i in x) result = c(result, any(i == y))
  result
}
```

```
# Version 2
x_in_y = function(x, y) {
  result = rep(NA, length(x))
  for(i in 1:length(x)) result[i] = any(x[i] == y)
  result
}
```

Loops

- In fact, we don't need to write a function such as `x_in_y` ourselves; we can use the `%in%` **operator**
- The `%in%` operator, with an expression `x %in% y`, returns a `logical` vector indicating the **presence** of each element of `x` in `y` -

```
1:5 %in% c(1, 2, 5)
## [1]  TRUE  TRUE FALSE FALSE  TRUE
```

```
1:5 %in% c(1, 2, 3, 5)
## [1]  TRUE  TRUE  TRUE FALSE  TRUE
```

```
c("a", "B", "c", "ee") %in% letters
## [1]  TRUE FALSE  TRUE FALSE
```

```
c("a", "B", "c", "ee") %in% LETTERS
## [1] FALSE  TRUE FALSE FALSE
```

Reading table from a file

- The table `rainfall.csv` contains average **monthly rainfall** data (based on the period 1980-2010) for September-May, in 169 meteorological stations in Israel
- The table also contains station **name**, station **number**, **elevation** and **X-Y** coordinates

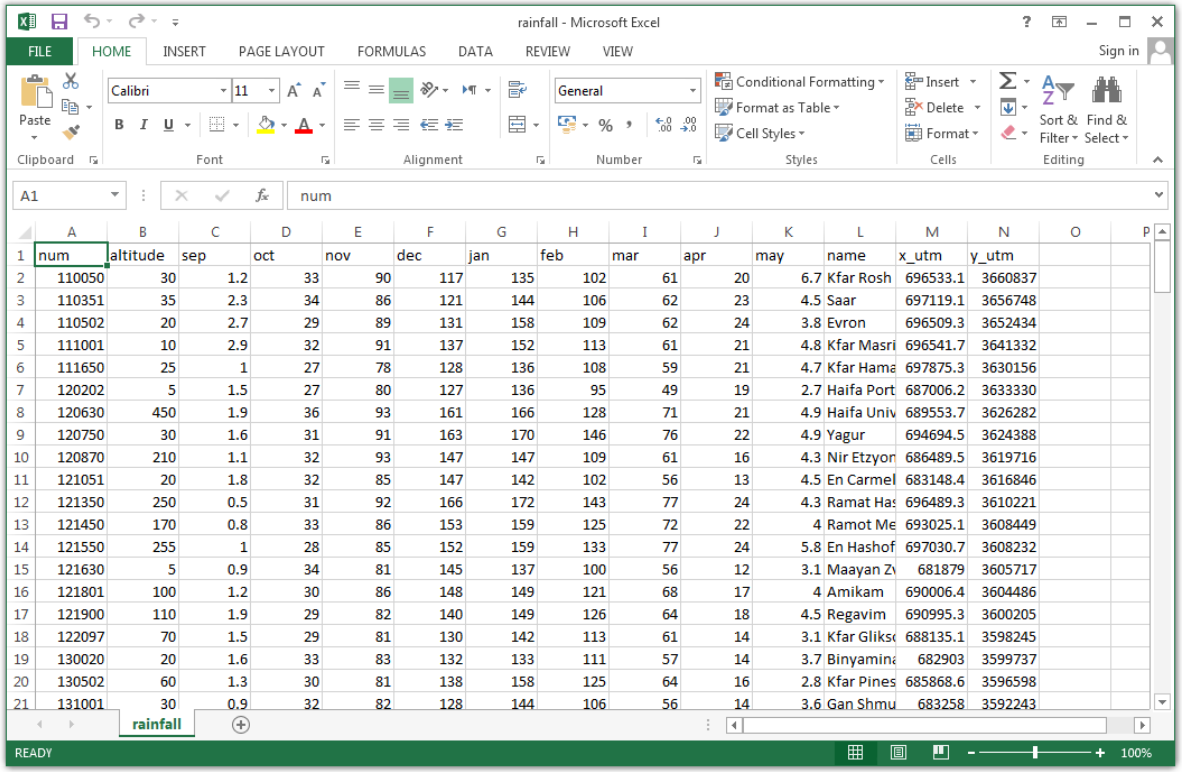

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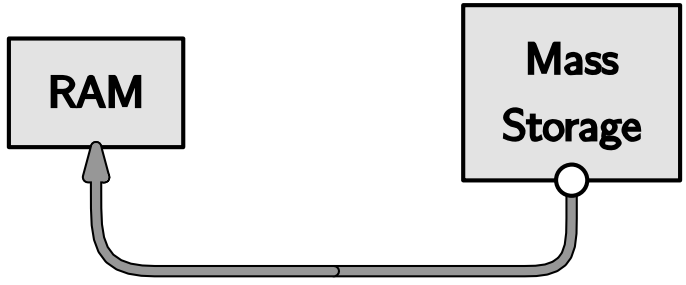
Figure 3: `rainfall.csv` opened in Excel

Reading table from a file

- In addition to creating a table with `data.frame`, we can read an existing table **from disk**, such as from a Comma-Separated Values (CSV) file
- We can read a CSV file with `read.csv` -

```
# Windows
read.csv("C:\\Data2\\rainfall.csv")
read.csv("C:/Data2/rainfall.csv")

# Mac / Linux
read.csv("~/Dropbox/Data2/rainfall.csv")
```



Reading table from a file

- Note: the separating character on Windows is / or \\, not the familiar \
- In case the file path uses the **incorrect separator** \ we get an error -

```
read.csv("C:\Data2\rainfall.csv")
## Error: '\D' is an unrecognized escape in character stri
```

- In case the file **does not exist** we get a different error -

```
read.csv("C:\\Data2\\rainfall.csv")
## Warning in file(file, "rt"): cannot open file 'C:
## \Data2\rainfall.csv': No such file or directory
## Error in file(file, "rt"): cannot open the connection
```

Reading table from a file

- The `stringsAsFactors` parameter of `read.csv` (and several other functions) determines whether **text columns** are converted to `factor` (default is `TRUE`)
- Usually, we want to **avoid** the conversion with `stringsAsFactors=FALSE`

```
read.csv(
  "~/Dropbox/Data2/rainfall.csv",
  stringsAsFactors = FALSE
)
```

Working directory

- R always points to a certain directory, knows as the **working directory**
- We can **get** the current working directory with `getwd` -

```
getwd()
## [1] "/home/michael/Dropbox/Data2"
```

- We can **set** a new working directory with `setwd` -

```
setwd("~/Dropbox/Data2")
```

- When **reading a file** from the working directory, we can specify just the **file name** instead of the full path -

```
read.csv("rainfall.csv")
```

data.frame structure

- Let's **read** the `rainfall.csv` file -

```
rainfall = read.csv(
  "rainfall.csv",
  stringsAsFactors = FALSE
)
```

data.frame structure

- We can also use the `head` or `tail` function which return a subset of the **first** or **last** several rows, respectively -

```
head(rainfall)
```

```
##      num altitude sep oct nov dec jan feb mar apr
## 1 110050       30 1.2  33  90 117 135 102  61  20
## 2 110351       35 2.3  34  86 121 144 106  62  23
## 3 110502       20 2.7  29  89 131 158 109  62  24
## 4 111001       10 2.9  32  91 137 152 113  61  21
## 5 111650       25 1.0  27  78 128 136 108  59  21
## 6 120202        5 1.5  27  80 127 136  95  49  19
##   may              name    x_utm   y_utm
## 1 6.7 Kfar Rosh Hanikra 696533.1 3660837
## 2 4.5              Saar 697119.1 3656748
## 3 3.8             Evron 696509.3 3652434
## 4 4.8       Kfar Masrik 696541.7 3641332
## 5 4.7     Kfar Hamakabi 697875.3 3630156
## 6 2.7        Haifa Port 687006.2 3633330
```

data.frame structure

- We can also use the `head` or `tail` function which return a subset of the **first** or **last** several rows, respectively -

```
tail(rainfall)
```

```
##         num altitude sep oct nov dec jan feb mar
## 164 321800     -180 0.2  12  37  55  65  59  36
## 165 321850     -220 0.2  13  33  53  64  56  35
## 166 330370     -375 0.1   6  10  20  22  19  11
## 167 337000     -390 0.0   5   3  10   7   7   7
## 168 345005       80 0.4   2   2   6   5   4   5
## 169 347702       11 0.0   4   2   5   4   3   3
##     apr may         name    x_utm   y_utm
## 164  11 5.0 Sde Eliyahu 736189.3 3591636
## 165  11 4.7   Tirat Zvi 737522.4 3590062
## 166   6 1.3       Kalya 733547.8 3515345
## 167   3 0.5        Sdom 728245.6 3435503
## 168   2 0.4     Yotveta 700626.3 3307819
## 169   2 1.0       Eilat 689139.3 3270290
```

data.frame structure

- We can check the table **structure** with `str` -

```
str(rainfall)
```

```
## 'data.frame':    169 obs. of  14 variables:
##  $ num     : int  110050 110351 110502 111001 111650 120202 120630 120750 12
##  $ altitude: int  30 35 20 10 25 5 450 30 210 20 ...
##  $ sep     : num  1.2 2.3 2.7 2.9 1 1.5 1.9 1.6 1.1 1.8 ...
##  $ oct     : int  33 34 29 32 27 27 36 31 32 32 ...
##  $ nov     : int  90 86 89 91 78 80 93 91 93 85 ...
##  $ dec     : int  117 121 131 137 128 127 161 163 147 147 ...
##  $ jan     : int  135 144 158 152 136 136 166 170 147 142 ...
##  $ feb     : int  102 106 109 113 108 95 128 146 109 102 ...
##  $ mar     : int  61 62 62 61 59 49 71 76 61 56 ...
##  $ apr     : int  20 23 24 21 21 19 21 22 16 13 ...
##  $ may     : num  6.7 4.5 3.8 4.8 4.7 2.7 4.9 4.9 4.3 4.5 ...
##  $ name    : chr  "Kfar Rosh Hanikra" "Saar" "Evron" "Kfar Masrik" ...
##  $ x_utm   : num  696533 697119 696509 696542 697875 ...
##  $ y_utm   : num  3660837 3656748 3652434 3641332 3630156 ...
```

`data.frame` structure

- Question: create a plot of rainfall in January (`jan`) as function of elevation (`altitude`) based on the `rainfall` table

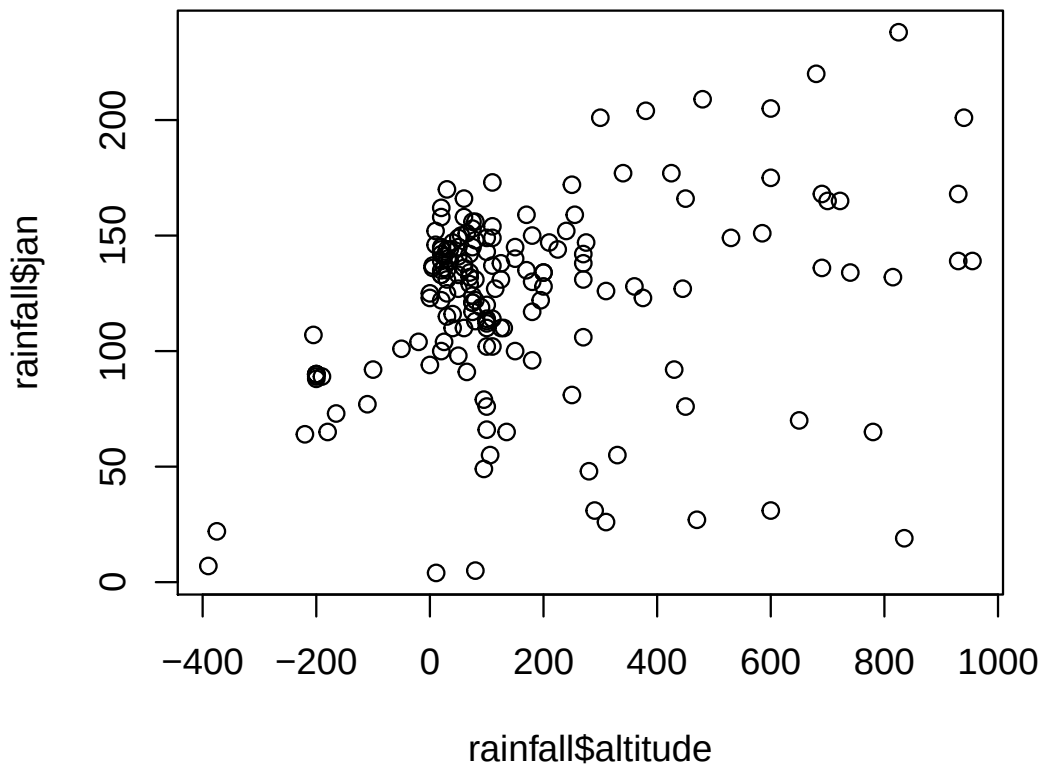


Figure 4: Rainfall in January as function of elevation

data.frame structure

- We can get specific information from the table trough **subsetting** and **summarizing**
- What is the elevation of the lowest and highest stations?

```
min(rainfall$altitude)
## [1] -390
```

```
max(rainfall$altitude)
## [1] 955
```

- What is the name of the lowest and highest station?

```
rainfall$name[which.min(rainfall$altitude)]
## [1] "Sdom"
```

```
rainfall$name[which.max(rainfall$altitude)]
## [1] "Rosh Tzurim"
```

data.frame structure

- How much rainfall does the "Haifa University" station receive in April?

```
rainfall$apr[rainfall$name == "Haifa University"]
## [1] 21
```

Creating new table columns

- We can create a **new column** through assignment -

```
rainfall$sep_oct = rainfall$sep + rainfall$oct
```

- To accomodate more complex calculations, we can also create a new column inside a `for` **loop** going over table **rows** -

```
m = c(
  "sep", "oct", "nov", "dec", "jan",
  "feb", "mar", "apr", "may"
)
for(i in 1:nrow(rainfall)) {
  rainfall$annual[i] = sum(rainfall[i, m])
}
```

Creating new table columns

```
head(rainfall)
```

```
##      num altitude sep oct nov dec jan feb mar apr may
## 1 110050       30 1.2  33  90 117 135 102  61  20 6.7
## 2 110351       35 2.3  34  86 121 144 106  62  23 4.5
## 3 110502       20 2.7  29  89 131 158 109  62  24 3.8
## 4 111001       10 2.9  32  91 137 152 113  61  21 4.8
## 5 111650       25 1.0  27  78 128 136 108  59  21 4.7
## 6 120202        5 1.5  27  80 127 136  95  49  19 2.7
##                 name    x_utm   y_utm sep_oct annual
## 1 Kfar Rosh Hanikra 696533.1 3660837    34.2  565.9
## 2              Saar 697119.1 3656748    36.3  582.8
## 3             Evron 696509.3 3652434    31.7  608.5
## 4       Kfar Masrik 696541.7 3641332    34.9  614.7
## 5     Kfar Hamakabi 697875.3 3630156    28.0  562.7
## 6        Haifa Port 687006.2 3633330    28.5  537.2
```

The `apply` function

- The `apply` function can **replace** `for` loops, in situations when we are interested in applying the **same function** on all subsets of certain **dimension** of a `data.frame`, a `matrix` or an `array`
- In case of a table, there are two **dimensions** we can work on -
  - **Rows** = Dimension 1
  - **Columns** = Dimension 2
- The `apply` function needs three arguments -
  - `X` - The **object** we are working on: `data.frame`, `matrix` or `array`
  - `MARGIN` - The **dimension** we are working on
  - `FUN` - The **function** applied on that dimension

The apply function

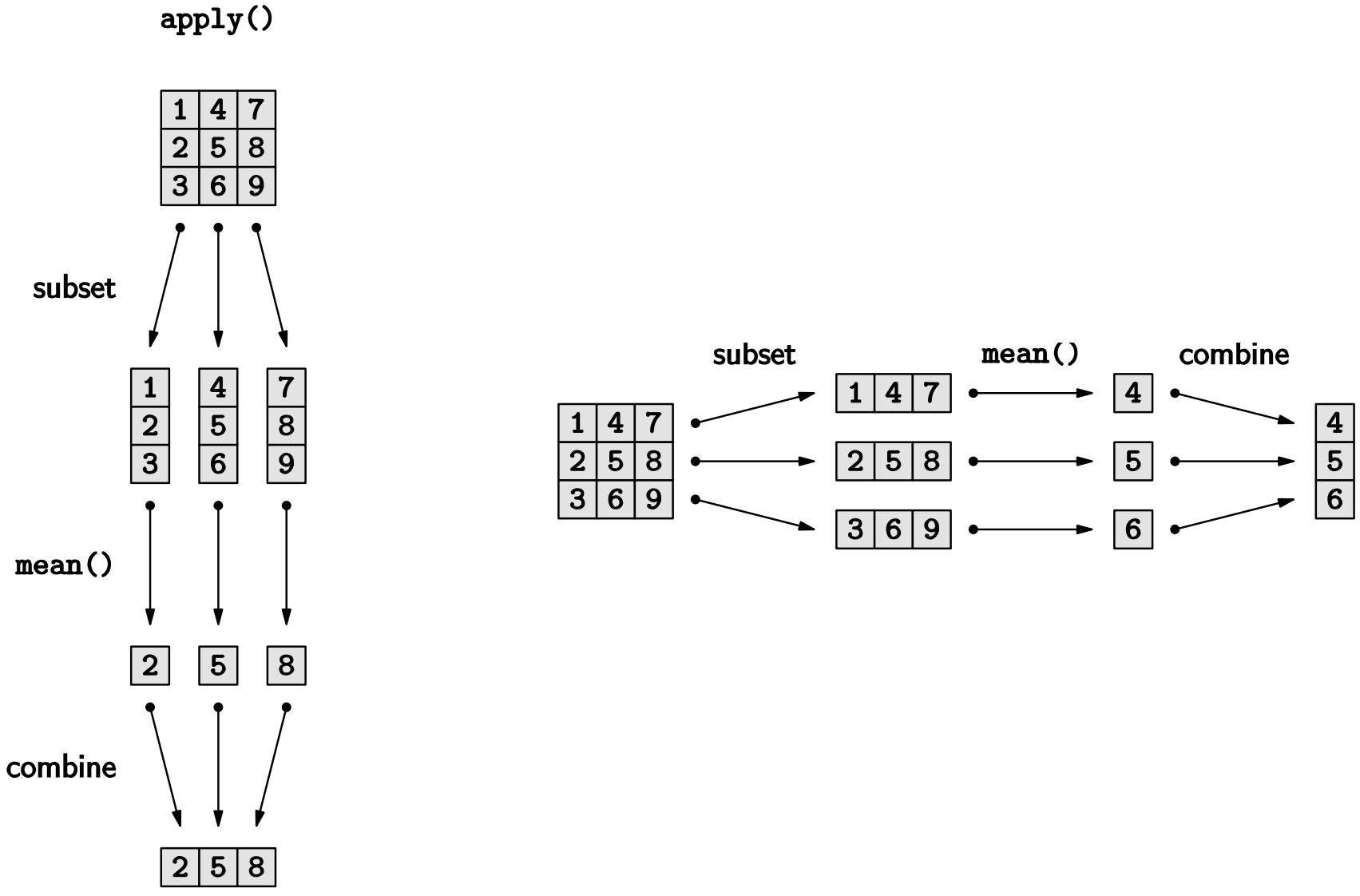


Figure 5: The apply function, operating on columns (left) or rows (rigth)

The apply function

- For example, the `apply` function can replace a `for` loop for calculating **average** annual rainfall **per station**
- The `sum` function is applied on the **rows** dimension -

```
rainfall$annual = apply(
  X = rainfall[, m],
  MARGIN = 1,
  FUN = sum
)
```

- As another example, we can calculate **average** monthly rainfall **per month**
- This time, the `mean` function is applied on the **columns** dimension -

```
avg_rain = apply(rainfall[, m], 2, mean)
```

The apply function

- The result `avg_rain` is a **named** `numeric` vector
- Element names correspond to **column** names of `X` -

```
avg_rain
##         sep         oct         nov         dec
##    1.025444   21.532544   64.852071 105.798817
##         jan         feb         mar         apr
## 123.053254 103.130178  58.366864  16.769231
##         may
##    3.968639
```

- We can quickly visualize the values with `barplot` -

```
barplot(avg_rain)
```

The apply function

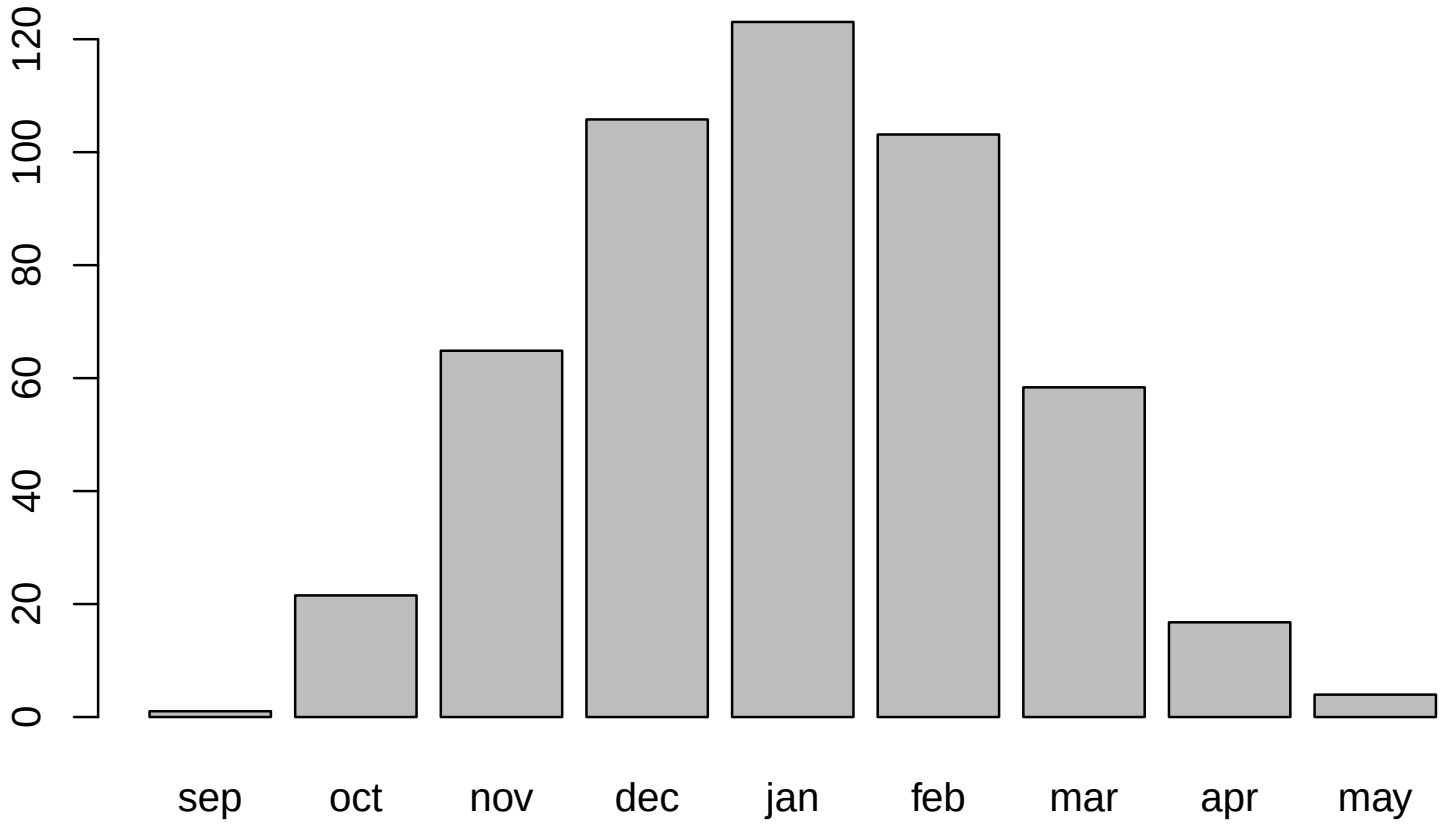


Figure 6: Average rainfall per month, among 169 stations in Israel

The apply function

- As another example, let's use apply to find the station **name** with the **highest** rainfall **per month**
- The following applies which.max on the columns, returning the row **indices** where the maximal rainfall values are located per column -

```
max_st = apply(rainfall[, m], 2, which.max)
max_st
## sep oct nov dec jan feb mar apr may
##  71  23  77  77  77  66  66  66  77
```

- We can get the corresponding station **names** by subsetting the name column using max_st -

```
rainfall$name[max_st]
## [1] "Eilon"       "Maabarot"    "Horashim"
## [4] "Horashim"    "Horashim"    "Golan Farm"
## [7] "Golan Farm" "Golan Farm" "Horashim"
```

The apply function

- It is convenient to **combine** the names and values in a table -

```
data.frame(
  month = m,
  name = rainfall$name[max_st],
  stringsAsFactors = FALSE
)
##   month         name
## 1   sep        Eilon
## 2   oct    Maabarot
## 3   nov    Horashim
## 4   dec    Horashim
## 5   jan    Horashim
## 6   feb Golan Farm
## 7   mar Golan Farm
## 8   apr Golan Farm
## 9   may    Horashim
```

Table join

- The `dates.csv` table contains the **dates** when each image in the raster `modis_south.tif`, which we will work with in **Lesson 05**, was taken -

```
dates = read.csv("dates.csv", stringsAsFactors = FALSE)
```

```
head(dates)
##   day month year
## 1  18     2 2000
## 2   5     3 2000
## 3  21     3 2000
## 4   6     4 2000
## 5  22     4 2000
## 6   8     5 2000
```

Table join

- For further analysis of the images we would like to be able to group them **by season**
- How can we calculate a new `season` **column**, specifying the season each date belongs to?

Table 2: Months and seasons

season	months
`"winter"`	12, 1, 2
`"spring"`	3, 4, 5
`"summer"`	6, 7, 8
`"fall"`	9, 10, 11

Table join

- One way is to **assign** each season name into a **subset** of a new `season` column -

```
dates$season[dates$month %in% c(12, 1:2)] = "winter"
dates$season[dates$month %in% 3:5] = "spring"
dates$season[dates$month %in% 6:8] = "summer"
dates$season[dates$month %in% 9:11] = "fall"
```

Table join

```
head(dates)
##   day month year season
## 1  18     2 2000 winter
## 2   5     3 2000 spring
## 3  21     3 2000 spring
## 4   6     4 2000 spring
## 5  22     4 2000 spring
## 6   8     5 2000 spring
```

- This method of classification may be inconvenient when we have many categories or complex criteria
- Another option is to use a **table join**

R packages

- All object definitions (including functions) in R are contained in **packages**
- To use a particular object, we need to -
  - **Install** the package with `install.packages` (once)
  - **Load** the package using the `library` function (in each new R session)
  - Loading a package basically means the code we downloaded is **executed**, loading all objects the package defined into the **RAM**
- All function calls we used until now did require this. Why? Because several packages are **installed** along with R and **loaded** on R start-up
- There are several more packages which are installed by default but **not loaded** on start-up (total of ~30)

R packages

Table 4-1. Packages included with R

Package name	Loaded by default	Description
base	✓	Basic functions of the R language, including arithmetic, I/O, programming support
boot		Bootstrap resampling
class		Classification algorithms, including nearest neighbors, self-organizing maps, and learning vector quantization
cluster		Clustering algorithms
codetools		Tools for analyzing R code
compiler		Byte code compiler for R
datasets	✓	Some famous data sets
foreign		Tools for reading data from other formats, including Stata, SAS, and SPSS files
graphics	✓	Functions for base graphics
grDevices	✓	Device support for base and grid graphics, including system-specific functions
grid		Tools for building more sophisticated graphics than the base graphics
KernSmooth		Functions for kernel smoothing
lattice		An implementation of Trellis graphics for R: prettier graphics than the default graphics
MASS		Functions and data used in the book *Modern Applied Statistics with S* by Venables and Ripley; contains a lot of useful statistics functions
methods	✓	Implementation of formal methods and classes introduced in S version 4 (called S4 methods and classes)
mgcv		Functions for generalized additive modeling and generalized additive mixed modeling
nlme		Linear and nonlinear mixed-effects models
nnet		Feed-forward neural networks and multinomial log linear models
parallel		Support for parallel computation, including random-number generation.
rpart		Tools for building recursive partitioning and regression tree models
spatial		Functions for Kriging and point pattern analysis
splines		Regression spline functions and classes
stats	✓	Functions for statistics calculations and random number generation; includes many common statistical tests, probability distributions, and modeling tools
stats4		Statistics functions as S4 methods and classes
survival		Survival analysis functions
tcltk		Interface to Tcl/Tk; used to create platform-independent UI tools
tools		Tools for developing packages
utils	✓	A variety of utility functions for R, including package management, file reading and writing, and editing

Figure 7: Packages included with R[1]

[1] R in a Nutshell, 2010

R packages

Table 4-1. Packages included with R

Package name	Loaded by default	Description
base	✓	Basic functions of the R language, including arithmetic, I/O, programming support
boot		Bootstrap resampling
class		Classification algorithms, including nearest neighbors, self-organizing maps, and learning vector quantization
cluster		Clustering algorithms
codetools		Tools for analyzing R code
compiler		Byte code compiler for R
datasets	✓	Some famous data sets
foreign		Tools for reading data from other formats, including Stata, SAS, and SPSS files
graphics	✓	Functions for base graphics
grDevices	✓	Device support for base and grid graphics, including system-specific functions
grid		Tools for building more sophisticated graphics than the base graphics
KernSmooth		Functions for kernel smoothing

R packages

- **Most** of the ~13,000 R packages (Sep 2018) are *not* installed by default
- To use one of these packages we first need to **install** it on the computer
- This is a **one-time** operation using the `install.packages` function
- After the package is installed, each time we want to use it we need to **load** it using `library`

R packages

- In the next example we use a package called `dplyr`
- This package is not installed with R, we need to **install** it ourselves -

```
install.packages("dplyr")
```

- Note: if the package is already installed then `install.packages` **overwrites** the old installation
- Once the package is already installed, we need to use the `library` function to **load** it into memory -

```
library(dplyr)
```

- Note: package name can be passed to `library` **without** quotes

Table join

- The `left_join` function from `dplyr` does a **left join** between tables
- The first two parameters are the **tables** that need to be joined, `x` and `y`
- The third `by` parameter is the common **column name(s)** by which the tables need to be joined

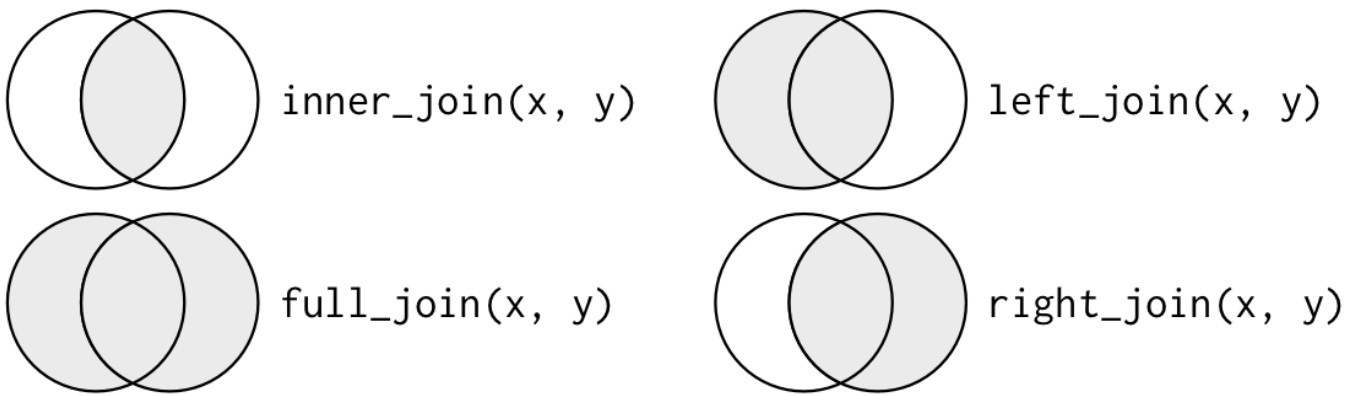


Figure 8: Join types[2]

[2] http://r4ds.had.co.nz/relational-data.html

Table join

- Next we prepare a table `tab` with the **classification** of months into seasons -

```
tab = data.frame(
  month = c(12, 1:11),
  season = rep(
    c("winter","spring","summer","fall"),
    each = 3
  ),
  stringsAsFactors = FALSE
)
```

Table join

- Next we prepare a table `tab` with the classification of months into seasons -

```
tab
```

```
##    month season
## 1     12 winter
## 2      1 winter
## 3      2 winter
## 4      3 spring
## 5      4 spring
## 6      5 spring
## 7      6 summer
## 8      7 summer
## 9      8 summer
## 10     9   fall
## 11    10   fall
## 12    11   fall
```

Table join

- Now we can **join** the `dates` and `tab` tables
- Before that, we **remove** the `season` column we manually created in the previous example -

```
dates$season = NULL
dates = left_join(dates, tab, by = "month")
```

```
head(dates)
##   day month year season
## 1  18     2 2000 winter
## 2   5     3 2000 spring
## 3  21     3 2000 spring
## 4   6     4 2000 spring
## 5  22     4 2000 spring
## 6   8     5 2000 spring
```

Dates

- To get a **date** column we can paste the `year`, `month` and `day` columns and apply `as.Date` -

```
dates$date = as.Date(
  paste(dates$year, dates$month, dates$day, sep = "-")
)
```

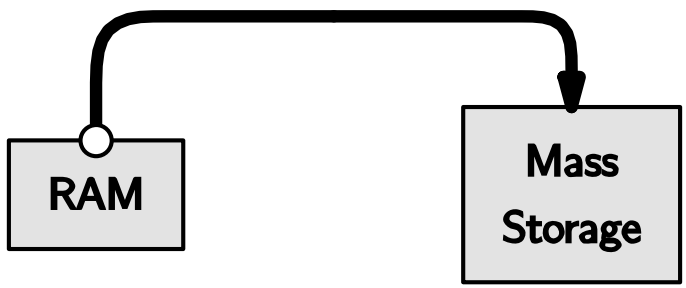
```
head(dates)
##   day month year season       date
## 1  18     2 2000 winter 2000-02-18
## 2   5     3 2000 spring 2000-03-05
## 3  21     3 2000 spring 2000-03-21
## 4   6     4 2000 spring 2000-04-06
## 5  22     4 2000 spring 2000-04-22
## 6   8     5 2000 spring 2000-05-08
```

Writing table to file

- Using `write.csv` we can **write** the contents of a `data.frame` to a **CSV file** -

```
write.csv(dates, "dates2.csv", row.names = FALSE)
```

- The `row.names` parameter determines whether the **row names** are saved
- Note: like in `read.csv`, we can either give a **full** file path or just the **file name**; if the specify just the file name then the file is written to the **working directory**



Exercise 2 - Submission date **2018-12-09**

Introduction to Spatial Data Programming

Execrise 2

Time series and function definition

& Tables, conditionals and loops

Last updated: 2018-10-03 08:46:52

Question 1

- Run the following four expressions to load two vectors named `year` and `co2` into memory

```
data(co2)
means = aggregate(co2, FUN = mean)
year = as.vector(time(means))
co2 = as.vector(means)
```

- The `co2` vector contains CO_2 measurements in the atmosphere, in *ppm* units, during the period 1959-1997. The `year` vector contains the corresponding years
- Assuming that the rate of CO_2 increase was constant and equal to the average rate during 1959-1997, calculate the predicted CO_2 concentration during each of the years 1998-2017
- Create a **plot** showing CO_2 concentration as function of time, with -
  - Observed values during 1959-1997, based on the `year` and `co2` vectors, in **black**
  - Predicted values during 1998-2017 in **blue**
- **Add** a point in **red** showing the true concentration in 2017, which was `406.53`