Advanced Research Methods - E7004

Day 1 - Introduction

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Summary

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NOTE

This document has been written using R Markdown. More info on R Markdown syntax at:

basic-writing-and-formatting-syntax

Markdown-Here-Cheatsheet

rmarkdown-cheatsheet

rmarkdown-reference

Introduction

R is a powerful object-oriented programming language, specifically designed for statistics. Object-oriented means that we can assign data to named objects and use them for computations.

It is free and open-source and can be downloaded for free at: CRAN

I also suggest to download R Studio, which makes writing code much easier: R-Studio

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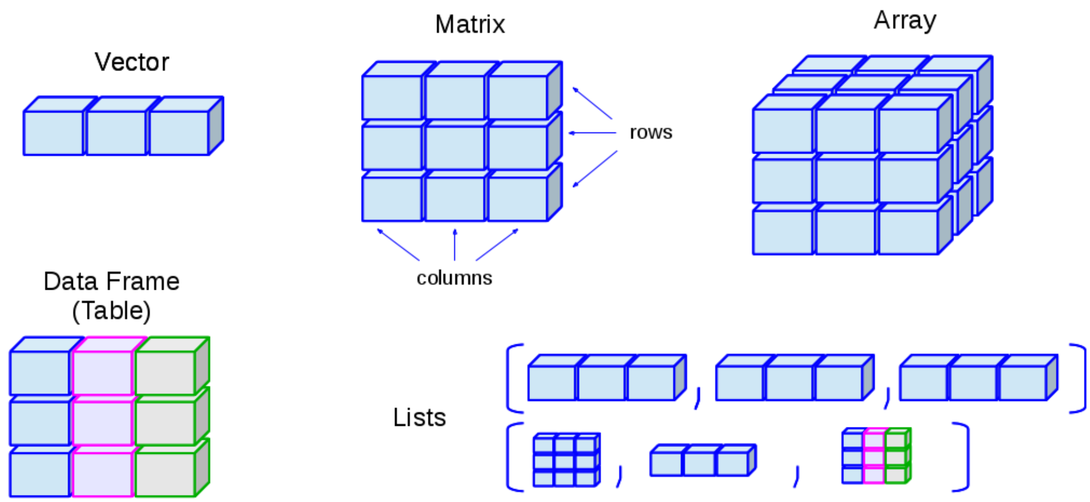
Data Structures

More info on data structures here: venus.ifca.unican.es

The most important data structures are vector, matrix, data.frame and lists (array is not used much)



Vectors

Vectors are simply 1D arrays of any type, e.g. numerical, categorical or strings.

```
A = rnorm(n=20, mean=4, sd=1)

A

##  [1] 2.573677 2.558899 3.096980 2.594867 3.354332 5.600710 3.874753
##  [8] 2.486332 3.760324 2.562872 3.408074 5.216458 1.806027 2.368082
## [15] 4.513093 3.086741 4.505166 5.083187 2.377797 4.499632
```

A is a vector with 40 elements. We created this vector by using the function `rnorm`, which randomly samples `n = 20` numerical values from a normal distribution (`mean = 4, sd = 1`)

```
length(A)

## [1] 20
```

We can obtain the length, i.e. the number of elements, in the vector using the function `length`. `A` is an object, specifically a 1D array also referred to as `vector` in R, and it can be used as such for analysis:

```
B = A + 3

B
```

```
##  [1] 5.573677 5.558899 6.096980 5.594867 6.354332 8.600710 6.874753
##  [8] 5.486332 6.760324 5.562872 6.408074 8.216458 4.806027 5.368082
## [15] 7.513093 6.086741 7.505166 8.083187 5.377797 7.499632
```

This expression adds the number 3 to each element of the `vector`, and stores this new `vector` into an object named `B`.

Matrix

Data can also be stored into more complex objects, like `matrix` and `data.frame`:

```
M = matrix(1:40, nrow=8, ncol=5)
```

This line creates a 8x5 `matrix`, which is a 2D object with a total of 40 elements.

We can look at it using the function `print`:

```
print(M)
```

```
##      [,1] [,2] [,3] [,4] [,5]
## [1,]    1    9   17   25   33
## [2,]    2   10   18   26   34
## [3,]    3   11   19   27   35
## [4,]    4   12   20   28   36
## [5,]    5   13   21   29   37
## [6,]    6   14   22   30   38
## [7,]    7   15   23   31   39
## [8,]    8   16   24   32   40
```

Please notice the way R fills the matrix. It does so by column. We can change that using the option `byrow`:

```
M = matrix(1:40, nrow=8, ncol=5, byrow=T)
print(M)
```

```
##      [,1] [,2] [,3] [,4] [,5]
## [1,]    1    2    3    4    5
## [2,]    6    7    8    9   10
## [3,]   11   12   13   14   15
## [4,]   16   17   18   19   20
## [5,]   21   22   23   24   25
## [6,]   26   27   28   29   30
## [7,]   31   32   33   34   35
## [8,]   36   37   38   39   40
```

The function `help` can be very useful when we are not familiar with options available:

```
help(matrix)
```

Data.Frame

Other important objects are `data.frame`:

```r
head(iris)
```

```
##   Sepal.Length Sepal.Width Petal.Length Petal.Width Species
## 1          5.1         3.5          1.4         0.2  setosa
## 2          4.9         3.0          1.4         0.2  setosa
## 3          4.7         3.2          1.3         0.2  setosa
## 4          4.6         3.1          1.5         0.2  setosa
## 5          5.0         3.6          1.4         0.2  setosa
## 6          5.4         3.9          1.7         0.4  setosa
```

`iris` is one of the numerous datasets freely available in R that we can use for testing. The function `head` allows us to just look at the first few rows of the dataset.

As you can see this object has multiple columns and many rows, but the entries are not only `numeric`.

```r
str(iris)
```

```
## 'data.frame':    150 obs. of  5 variables:
##  $ Sepal.Length: num  5.1 4.9 4.7 4.6 5 5.4 4.6 5 4.4 4.9 ...
##  $ Sepal.Width : num  3.5 3 3.2 3.1 3.6 3.9 3.4 3.4 2.9 3.1 ...
##  $ Petal.Length: num  1.4 1.4 1.3 1.5 1.4 1.7 1.4 1.5 1.4 1.5 ...
##  $ Petal.Width : num  0.2 0.2 0.2 0.2 0.2 0.4 0.3 0.2 0.2 0.1 ...
##  $ Species     : Factor w/ 3 levels "setosa","versicolor",..: 1 1 1 1 1 1
1 1 1 1 ...
```

The function `str` allows us to visualize the structure of any object, and it is particularly useful for `data.frame`. It tells us that this dataset has 150 observations (rows) and 5 variables (columns). It also tell us that the first 4 variables are numerical (`num`), while the last is categorical (or factorial).

Other types of variables could be logical (e.g. `TRUE` or `FALSE`), or strings (e.g. "TEST")

List

The last data structure we are going to look at is `list`. This structure allows to store diverse data types:

```r
L = list(A, M)
print(L)
```

```
## [[1]]
##  [1] 2.573677 2.558899 3.096980 2.594867 3.354332 5.600710 3.874753
##  [8] 2.486332 3.760324 2.562872 3.408074 5.216458 1.806027 2.368082
## [15] 4.513093 3.086741 4.505166 5.083187 2.377797 4.499632
##
## [[2]]
##      [,1] [,2] [,3] [,4] [,5]
## [1,]    1    2    3    4    5
## [2,]    6    7    8    9   10
## [3,]   11   12   13   14   15
```

```
## [4,]   16   17   18   19   20
## [5,]   21   22   23   24   25
## [6,]   26   27   28   29   30
## [7,]   31   32   33   34   35
## [8,]   36   37   38   39   40
```

This list has two elements, the first is a `vector` while the second is a `matrix`.

Subsetting

We can use square brackets to extract elements from all data structures. However, the syntax changes between objects.

`Vector` are 1D arrays so we can extract elements just by specifying the position along the `vector` we want to extract, starting from 1 up to `length(vector)`:

```
A[1]

## [1] 2.573677
```

This extracts the first element of the `vector`.

```
A[length(A)]

## [1] 4.499632
```

This extracts the last element, in position equal to `length(A)`, which is 40.

For `matrix` and `data.frame`, since these are 2D objects, we need to specify both a row and a column to extract:

```
M[3,5]

## [1] 15

iris[4,4]

## [1] 0.2
```

We can also extract multiple elements:

```
iris[1:4, 2]

## [1] 3.5 3.0 3.2 3.1
```

This line extracts from row 1 to row 4, but only elements in column 2.

We can also extract entire rows or columns. For example:

```
M[1,]

## [1] 1 2 3 4 5
```

extracts the whole row 1. While:

```
M[,3]

## [1]  3  8 13 18 23 28 33 38
```

extracts the whole column 3.

In a `data.frame` we can also extract columns by name:

```
iris$Sepal.Length

##   [1] 5.1 4.9 4.7 4.6 5.0 5.4 4.6 5.0 4.4 4.9 5.4 4.8 4.8 4.3 5.8 5.7 5.4
##  [18] 5.1 5.7 5.1 5.4 5.1 4.6 5.1 4.8 5.0 5.0 5.2 5.2 4.7 4.8 5.4 5.2 5.5
##  [35] 4.9 5.0 5.5 4.9 4.4 5.1 5.0 4.5 4.4 5.0 5.1 4.8 5.1 4.6 5.3 5.0 7.0
##  [52] 6.4 6.9 5.5 6.5 5.7 6.3 4.9 6.6 5.2 5.0 5.9 6.0 6.1 5.6 6.7 5.6 5.8
##  [69] 6.2 5.6 5.9 6.1 6.3 6.1 6.4 6.6 6.8 6.7 6.0 5.7 5.5 5.5 5.8 6.0 5.4
##  [86] 6.0 6.7 6.3 5.6 5.5 5.5 6.1 5.8 5.0 5.6 5.7 5.7 6.2 5.1 5.7 6.3 5.8
## [103] 7.1 6.3 6.5 7.6 4.9 7.3 6.7 7.2 6.5 6.4 6.8 5.7 5.8 6.4 6.5 7.7 7.7
## [120] 6.0 6.9 5.6 7.7 6.3 6.7 7.2 6.2 6.1 6.4 7.2 7.4 7.9 6.4 6.3 6.1 7.7
## [137] 6.3 6.4 6.0 6.9 6.7 6.9 5.8 6.8 6.7 6.7 6.3 6.5 6.2 5.9
```

For lists, since these are complex objects, we have two levels of extraction:

```
L[[1]]

##  [1] 2.573677 2.558899 3.096980 2.594867 3.354332 5.600710 3.874753
##  [8] 2.486332 3.760324 2.562872 3.408074 5.216458 1.806027 2.368082
## [15] 4.513093 3.086741 4.505166 5.083187 2.377797 4.499632
```

The first levels, identified by 2 square brackets, extracts the element of the list (in this case element 1, which is a vector). Then we can extract a particular element from the vector adding an additional level:

```
L[[1]][1]

## [1] 2.573677
```

The same would be true for the second element, which is a `data.frame`:

```
L[[2]][3,5]

## [1] 15
```

In this case, since the second element has both rows and columns, the second level of extraction needs to include two numbers.

Importing Data

In this course we will use data freely available on-line, which can be downloaded from: sheffield.ac.uk. A short description for each dataset is also available.

In case we have data stored locally, we first need to specify our working directory so that R knows where to load and save data. We can do that via the function `setwd`:

```
setwd("J:/Teaching_Harper/Advanced Research Methods - E7004/Possible
Datasets")
```

Please notice the forward slash (/) instead of the back slash we would normally use. Another way is go to Session->Set Working Directory directly in R Studio. Now we can import our data. The easiest way to import tables is from csv files.

This can also be done directly from the website:

```
Crimes =
read.csv("https://www.sheffield.ac.uk/polopoly_fs/1.569434!/file/stcp-
Rdataset-Crime.csv")

str(Crimes)

## 'data.frame':    47 obs. of  27 variables:
##  $ ï..CrimeRate       : num  45.5 52.3 56.6 60.3 64.2 67.6 70.5 73.2 75
78.1 ...
##  $ Youth              : int  135 140 157 139 126 128 130 143 141 133 ...
##  $ Southern           : int  0 0 1 1 0 0 0 0 0 0 ...
##  $ Education          : num  12.4 10.9 11.2 11.9 12.2 13.5 14.1 12.9 12.9
11.4 ...
##  $ ExpenditureYear0   : int  69 55 47 46 106 67 63 66 56 51 ...
##  $ LabourForce        : int  540 535 512 480 599 624 641 537 523 599 ...
##  $ Males              : int  965 1045 962 968 989 972 984 977 968 1024 ...
##  $ MoreMales          : int  0 1 0 0 0 0 0 0 0 1 ...
##  $ StateSize          : int  6 6 22 19 40 28 14 10 4 7 ...
##  $ YouthUnemployment  : int  80 135 97 135 78 77 70 114 107 99 ...
##  $ MatureUnemployment : int  22 40 34 53 25 25 21 35 37 27 ...
##  $ HighYouthUnemploy  : int  1 1 0 0 1 1 1 1 0 1 ...
##  $ Wage               : int  564 453 288 457 593 507 486 487 489 425 ...
##  $ BelowWage          : int  139 200 276 249 171 206 196 166 170 225 ...
##  $ CrimeRate10        : num  26.5 35.9 37.1 42.7 46.7 47.9 50.6 55.9 61.8
65.4 ...
##  $ Youth10            : int  135 135 153 139 125 128 153 143 153 134 ...
##  $ Education10        : num  12.5 10.9 11 11.8 12.2 13.8 14.1 13 12.9 11.2
...
##  $ ExpenditureYear10  : int  71 54 44 41 97 60 57 63 54 47 ...
##  $ LabourForce10      : int  564 540 529 497 602 621 641 549 538 600 ...
##  $ Males10            : int  974 1039 959 983 989 983 993 973 968 1024 ...
##  $ MoreMales10        : int  0 1 0 0 0 0 0 0 0 1 ...
##  $ StateSize10        : int  6 7 24 20 42 28 14 11 5 7 ...
##  $ YouthUnemploy10    : int  82 138 98 131 79 81 71 119 110 97 ...
##  $ MatureUnemploy10   : int  20 39 33 50 24 24 23 36 36 28 ...
##  $ HighYouthUnemploy10: int  1 1 0 0 1 1 1 1 1 1 ...
##  $ Wage10             : int  632 521 359 510 660 571 556 561 550 499 ...
##  $ BelowWage10        : int  142 210 256 235 162 199 176 168 126 215 ...
```

Please notice the name of the first variable `ï..CrimeRate`. This sometimes happens in R, which probably has some issues with this particular file. It is important to notice this, because we always need to use accurate variable names in R, otherwise the script will not work. We can find the description of the dataset at this link: Crime_data_summary

Even though reading csv is the easiest way to import data, there are many other formats of data that can be imported into R (e.g. Excel sheet). To find out more on how to import different formats of data please look at the links below:

Quick-R

DataCamp

Descriptive Statistics

Descriptive statistics is a basic technique that is used to describe a dataset.
This technique relies on indexes to capture important features of the dataset, such as mean and standard deviation, which will help us to compare it with other data.

Centrality

The most popular index of centrality is the mean, or arithmetic average:

$$\overline{y} = \frac{1}{n} \times \sum_{i=1}^{n} y_i$$

where $\overline{y}$ is the mean of a variable y, and n is the number of elements in y.

Note

The previous equation was written using the Latex syntax. More info here: Latex Equation Reference

---

The function `mean` can be used in R to compute the arithmetic average:

```
mean(Crimes$ï..CrimeRate)

## [1] 102.8085
```

Another useful measure of centrality is the median, which is defined as the middle value of a series of numbers, listed in numerical order. We can simply compute it using the function `median` in R:

```
median(Crimes$ï..CrimeRate)
```

```
## [1] 103
```

Spread

The Variance is a measure of spread and indicates the average amount of dispersion, i.e. distance from the mean, of each value in a dataset. It can be simply computed as follows:

$$s^2 = \frac{1}{n-1} \times \sum_{i=1}^{n} (y_i - \overline{y})^2$$

By definition, the variance is sum of the square differences between each observation y_i and the mean $\overline{y}$, divided by the number of observations minus 1.

In R, the variance can be simply computed as follows:

```
var(Crimes$ï..CrimeRate)

## [1] 834.8208
```

The Standard Deviation (s) is the square root of the variance:

```
sd(Crimes$ï..CrimeRate)

## [1] 28.89327
```

Summary

Sometimes, instead of computing indexes for a single variable we are more interested in looking at the whole dataset at once. We can do that with the function `summary`:

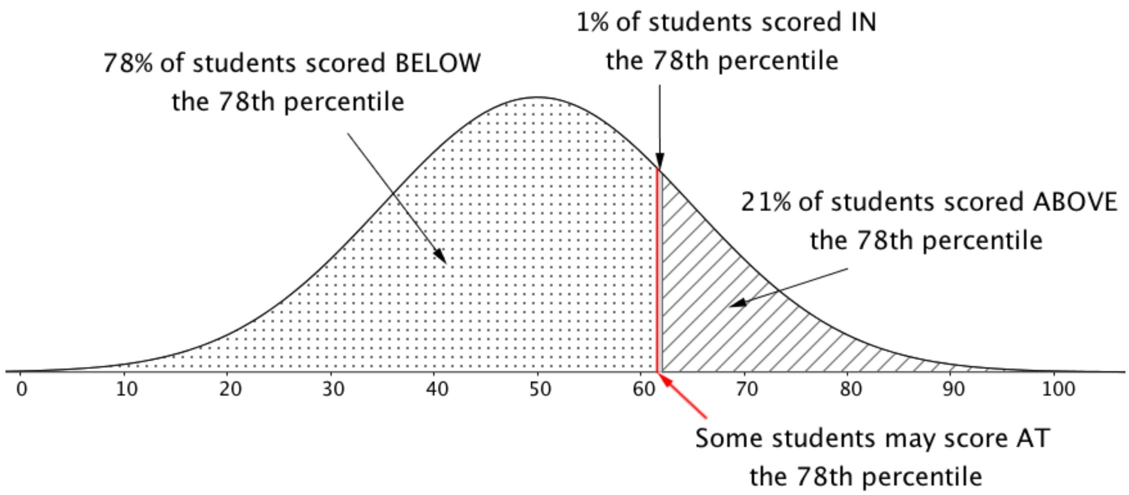
```
summary(Crimes)

##   ï..CrimeRate        Youth          Southern         Education    
##  Min.   : 45.5   Min.   :119.0   Min.   :0.0000   Min.   :10.00  
##  1st Qu.: 82.7   1st Qu.:130.0   1st Qu.:0.0000   1st Qu.:11.55  
##  Median :103.0   Median :136.0   Median :0.0000   Median :12.40  
##  Mean   :102.8   Mean   :138.6   Mean   :0.3404   Mean   :12.39  
##  3rd Qu.:120.7   3rd Qu.:146.0   3rd Qu.:1.0000   3rd Qu.:13.20  
##  Max.   :161.8   Max.   :177.0   Max.   :1.0000   Max.   :15.10  
##  ExpenditureYear0  LabourForce        Males          MoreMales     
##  Min.   : 45.0    Min.   :480.0   Min.   : 934.0   Min.   :0.0000  
##  1st Qu.: 62.5    1st Qu.:530.5   1st Qu.: 964.5   1st Qu.:0.0000  
##  Median : 78.0    Median :560.0   Median : 977.0   Median :0.0000  
##  Mean   : 85.0    Mean   :561.2   Mean   : 983.0   Mean   :0.1915  
##  3rd Qu.:104.5    3rd Qu.:593.0   3rd Qu.: 992.0   3rd Qu.:0.0000  
##  Max.   :166.0    Max.   :641.0   Max.   :1071.0   Max.   :1.0000  
##    StateSize       YouthUnemployment MatureUnemployment HighYouthUnemploy
##  Min.   :  3.00   Min.   : 70.00    Min.   :20.00      Min.   :0.0000   
##  1st Qu.: 10.00   1st Qu.: 80.50    1st Qu.:27.50      1st Qu.:0.0000   
##  Median : 25.00   Median : 92.00    Median :34.00      Median :0.0000   
##  Mean   : 36.62   Mean   : 95.47    Mean   :33.98      Mean   :0.3191   
```

```
##  3rd Qu.: 41.50   3rd Qu.:104.00    3rd Qu.:38.50      3rd Qu.:1.0000  
##  Max.   :168.00   Max.   :142.00    Max.   :58.00      Max.   :1.0000  
##       Wage         BelowWage      CrimeRate10        Youth10     
##  Min.   :288.0   Min.   :126.0   Min.   : 26.50   Min.   :120.0  
##  1st Qu.:459.5   1st Qu.:165.5   1st Qu.: 76.35   1st Qu.:134.0  
##  Median :537.0   Median :176.0   Median :103.50   Median :139.0  
##  Mean   :525.4   Mean   :194.0   Mean   :102.07   Mean   :140.5  
##  3rd Qu.:591.5   3rd Qu.:227.5   3rd Qu.:130.25   3rd Qu.:151.5  
##  Max.   :689.0   Max.   :276.0   Max.   :178.20   Max.   :164.0  
##   Education10     ExpenditureYear10 LabourForce10      Males10      
##  Min.   :10.10   Min.   : 41.00    Min.   :497.0   Min.   : 935.0  
##  1st Qu.:11.55   1st Qu.: 58.50    1st Qu.:538.0   1st Qu.: 969.5  
##  Median :12.40   Median : 73.00    Median :563.0   Median : 983.0  
##  Mean   :12.40   Mean   : 80.23    Mean   :565.5   Mean   : 986.9  
##  3rd Qu.:13.25   3rd Qu.: 97.00    3rd Qu.:599.0   3rd Qu.: 994.0  
##  Max.   :15.20   Max.   :157.00    Max.   :641.0   Max.   :1079.0  
##   MoreMales10      StateSize10     YouthUnemploy10   MatureUnemploy10
##  Min.   :0.0000   Min.   :  3.0   Min.   : 71.00   Min.   :15.00   
##  1st Qu.:0.0000   1st Qu.: 11.0   1st Qu.: 82.00   1st Qu.:28.00   
##  Median :0.0000   Median : 25.0   Median : 93.00   Median :34.00   
##  Mean   :0.2128   Mean   : 37.7   Mean   : 97.45   Mean   :33.36   
##  3rd Qu.:0.0000   3rd Qu.: 43.0   3rd Qu.:108.50   3rd Qu.:39.00   
##  Max.   :1.0000   Max.   :180.0   Max.   :143.00   Max.   :59.00   
##  HighYouthUnemploy10     Wage10        BelowWage10   
##  Min.   :0.0000      Min.   :359.0   Min.   :126.0  
##  1st Qu.:0.0000      1st Qu.:530.0   1st Qu.:165.0  
##  Median :0.0000      Median :615.0   Median :182.0  
##  Mean   :0.4043      Mean   :594.6   Mean   :193.0  
##  3rd Qu.:1.0000      3rd Qu.:659.5   3rd Qu.:229.5  
##  Max.   :1.0000      Max.   :748.0   Max.   :257.0  
```

This function returns several important information for all the variables in the `data.frame` `Crimes`. Beside mean and median, it also reports the minimum and maximum values, and the first and third quartiles, which are useful to understand the shape of the distribution.

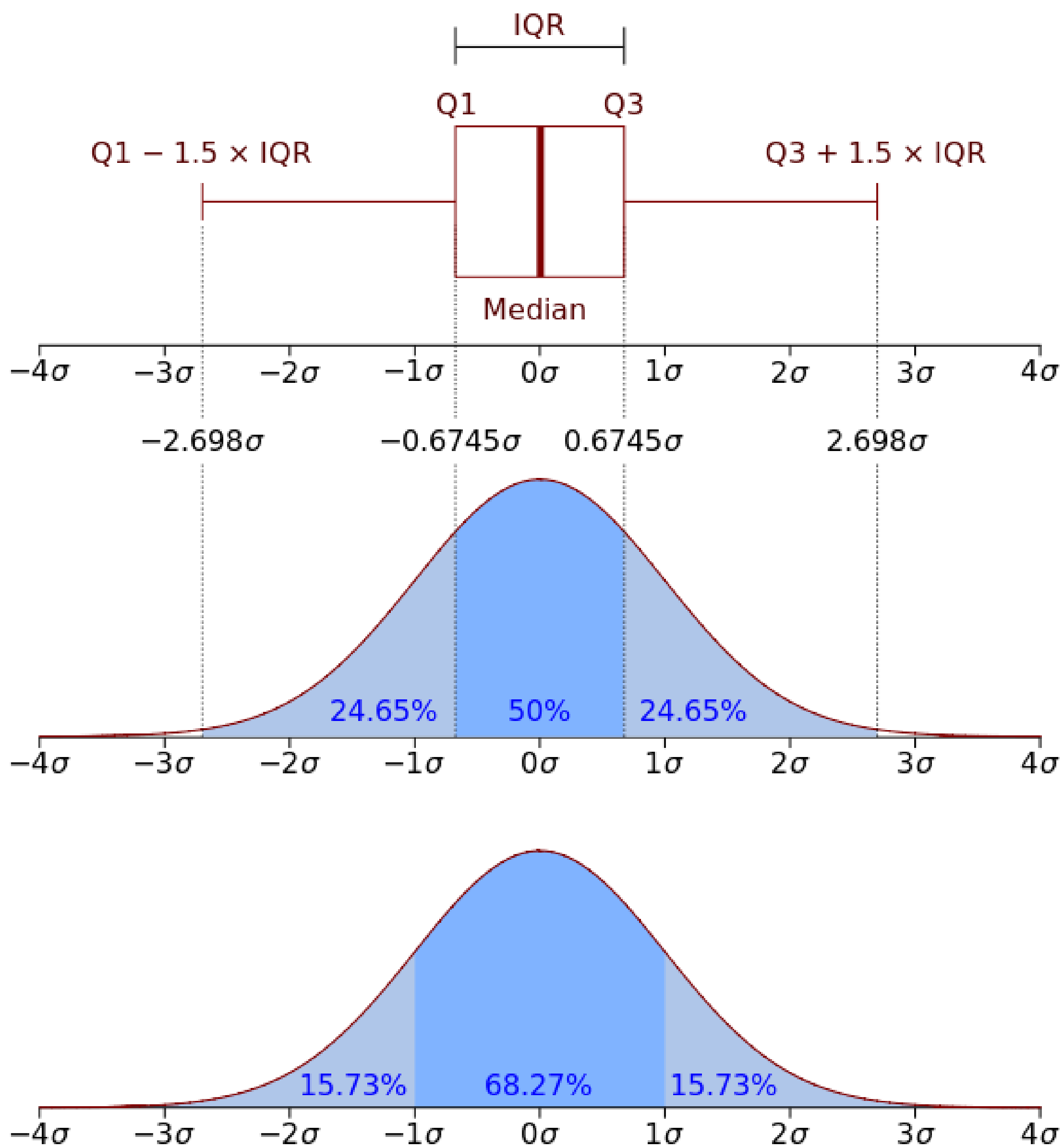
Quantiles

Quantiles are just cut points that divide the probability distribution into equal probability intervals:



Source: mathspace.co

In this example, the 78^{th} percentile is the point below which 78 of observations lie. Important for statistics is the division of the distribution into four parts, in this case we talk about quartiles. These are important because they allow to measure spread for non-normal distribution: using the distance between first and third quartiles (interquartile range):



Source: wikipedia

The interquartile range can be easily computed in R with the function `IQR`:

```
IQR(Crimes$ï..CrimeRate)

## [1] 37.95
```

Plotting

The final part of this lecture is dedicated to plotting. Plots are extremely important because they allow us to graphically represent our data, which is extremely important.

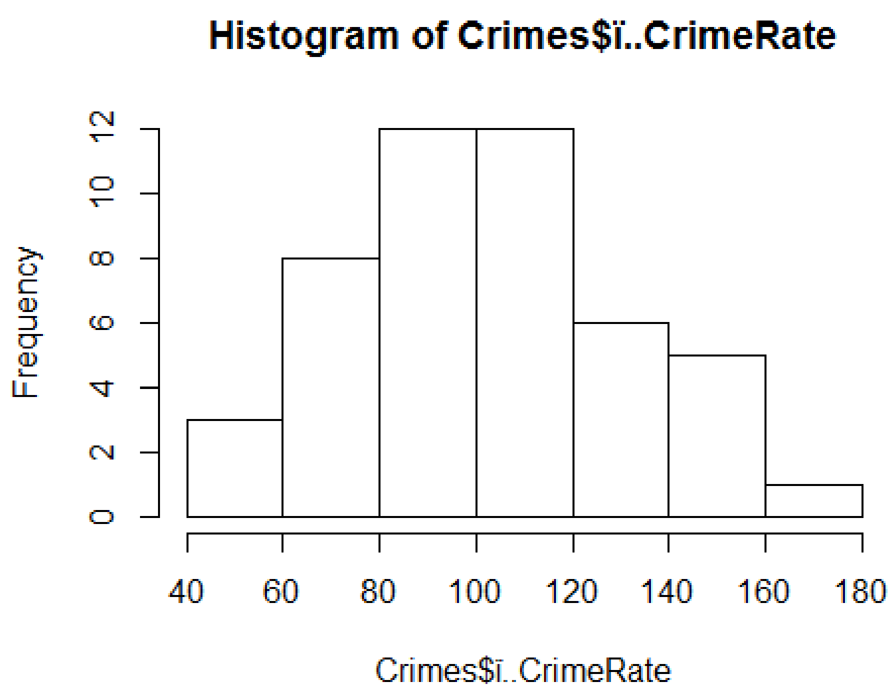
There are many useful plots that we will use throughout the course. In particular we will look at histograms and box-plots, which allows us to visualise and compare distributions; bar-charts, which are useful to develop hypothesis particularly for categorical data; and scatterplots, which are very useful to understand the relation between variables.

Histograms

Histograms are plots designed to represent distributions. To create a histogram we simply need to divide our data into non-overlapping “bins”, meaning small intervals, which will be plotted on the X axis. Then we count the number of values that fall into each bin, and this number is plotted on the Y axis.

Let’s look at an example, again using the `ï..CrimeRate` variable:

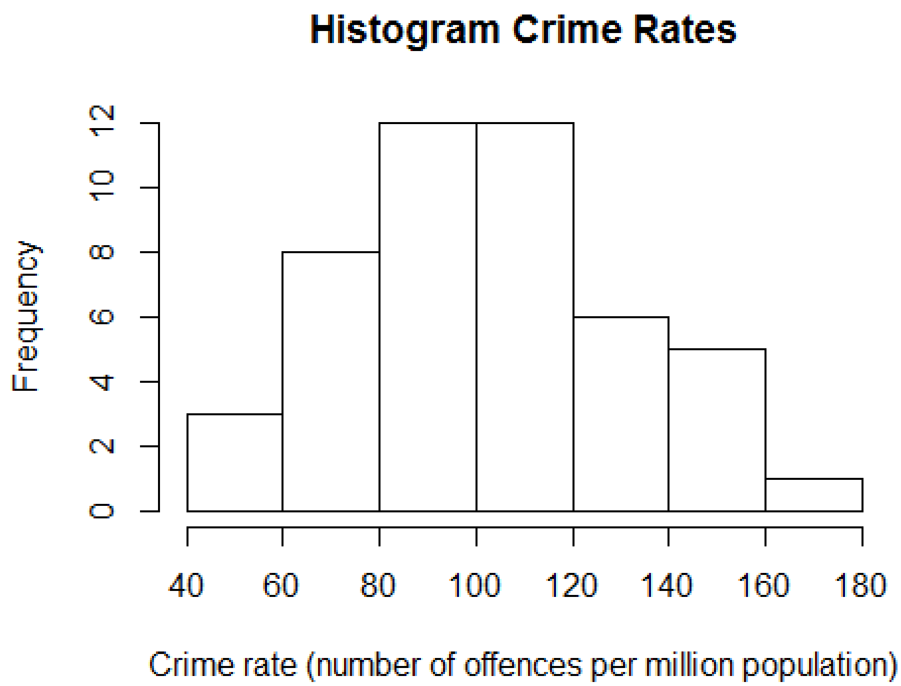
```
hist(Crimes$ï..CrimeRate)
```



As you can see the histogram has split the data into 7 bins, and plot the frequency (i.e. the number of values within each bin) on the Y axis.

We can add elements to this plots by changing title and the label for the X axis, with the options `main` and `xlab`:

```
hist(Crimes$ï..CrimeRate, main="Histogram Crime Rates", xlab="Crime rate
(number of offences per million population)")
```



As mentioned, histograms are very useful to check the shape of the distribution. For example, in this case we can see that the distribution is very close to normal, with its typical bell shape. This is extremely useful particularly when we will start looking at statistical tests. In fact, many tests are specifically designed to deal only with normally distributed data.

Bar Charts

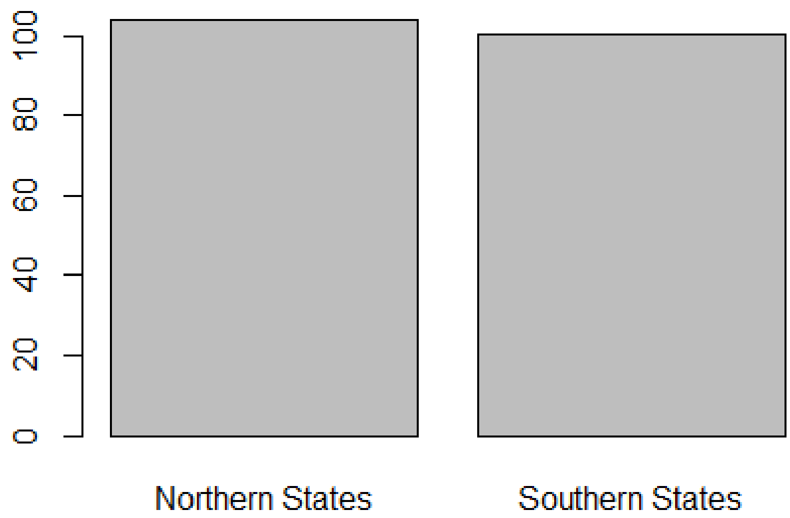
Bar charts are very useful when we need to compare groups. In the dataset Crimes there are variables that are binary, i.e. either 0 or 1. For example, `Southern` divides crimes reported in Southern (1) and Northern (0) states. Let's say we want to compare average crimes in both areas. For this task bar charts are the right tools.

Before we can plot the data we need to compute averages for both categories in the variable `Southern`. We can do it with the function `tapply`:

```
Mean = tapply(X=Crimes$ï..CrimeRate, INDEX=Crimes$Southern, FUN=mean)
Mean

##        0        1
## 103.9065 100.6813
```

The function `tapply`, applies a function (`FUN`) to a continuous variable (`X`), divided by groups (`INDEX`). Once we have the mean we can plot bars using `barplot`:

```
barplot(Mean, names.arg=c("Northern States", "Southern States"))
```



It seems Northern states have slightly more crimes.

We can provide more details on the plot by creating error bars, for example using the standard error of the mean. The standard error is computed as follows:

$$SEM = \frac{s}{\sqrt{n}}$$

where s is the standard deviation, and n is the number of samples.

In base R there is no function to compute the standard error, but we can create one:

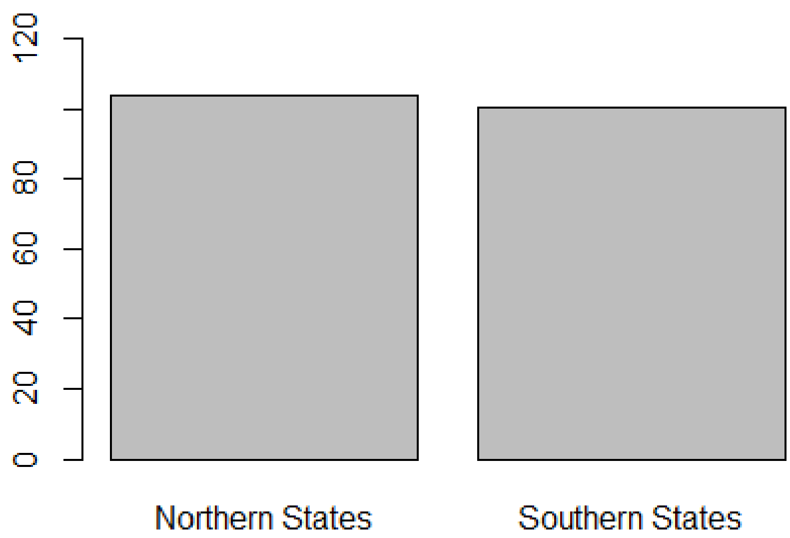
```
SEM = function(x){sd(x) / sqrt(length(x))}
```

This simple function will accept a vector `x`, as only input. Then it will compute the standard error as a ratio between the standard deviation (`sd`), and the square root (`sqrt`) of the number of elements (`length`) of the vector `x`. Now that we have a function we can again use `tapply`, to compute standard errors for each category:

```
SEM.STATES = tapply(X=Crimes$ï..CrimeRate, INDEX=Crimes$Southern, FUN=SEM)
SEM.STATES

##        0        1
## 5.739746 5.647058
```

These can be added to the plot with `segments` and `arrows`. However, we first need to recall the plot and save it into an object:

```r
BC_PLOT = barplot(Mean, names.arg=c("Northern States", "Southern States"),
ylim=c(0,120))
```

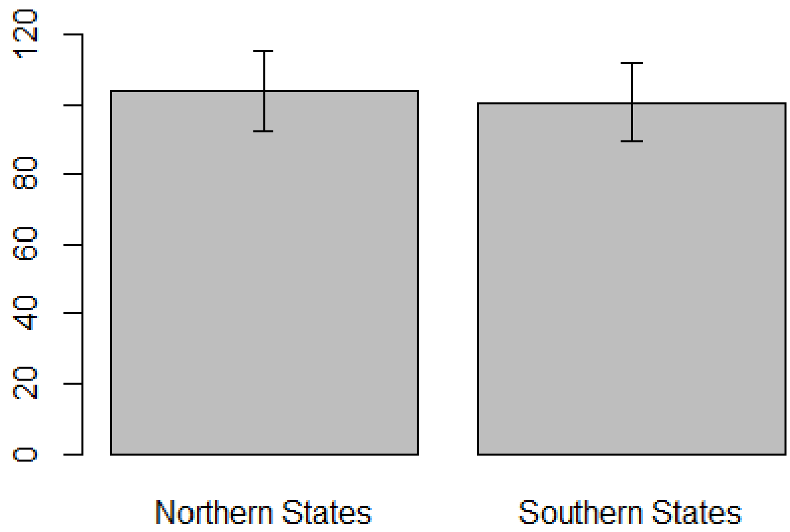


The object `BC_PLOT` now contains the plot, and in particular the coordinates of the two bars. We also added the option `ylim`, to manually set the range of the Y axis. This way we can make sure the error bars are fully visible.

```r
BC_PLOT

##       [,1]
## [1,]  0.7
## [2,]  1.9
```

With these numbers we can specify where to insert the error bars, as twice the standard error of the mean:

```r
BC_PLOT = barplot(Mean, names.arg=c("Northern States", "Southern States"),
ylim=c(0,120))

segments(x0=BC_PLOT, y0=Mean - (2*SEM.STATES), x1=BC_PLOT, y1=Mean +
(2*SEM.STATES), lwd=1.5)

arrows(x0=BC_PLOT, y0=Mean - (2*SEM.STATES), x1=BC_PLOT, y1=Mean +
(2*SEM.STATES), lwd=1.5, angle=90, code=3, length=0.05)
```



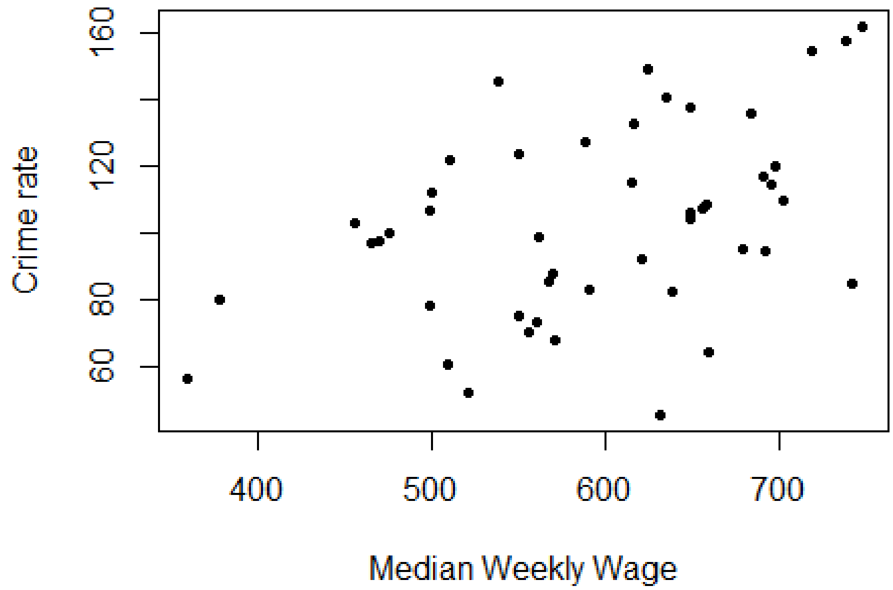
To know more about the code in the last two functions please refer to: www.r-bloggers.com/building-barplots-with-error-bars/

Plotting confidence intervals around the mean is extremely useful since it may provide good indications of statistical differences between groups. In fact, SEM is used in inferential statistics to compare groups. If two error bars are overlapping there are good chances that with a formal test the two groups will not result statistically different. This is something we can use to formulate our hypothesis before applying any statistical test.

Scatterplot

Scatterplots allows us to visualise the relation between two continuous variables. For example, let's say we want to visualise the relation between Crime rate and Wages, we can do that simply by:

```
plot(ï..CrimeRate ~ Wage10, data=Crimes, pch=20, xlab="Median Weekly Wage",
ylab="Crime rate")
```



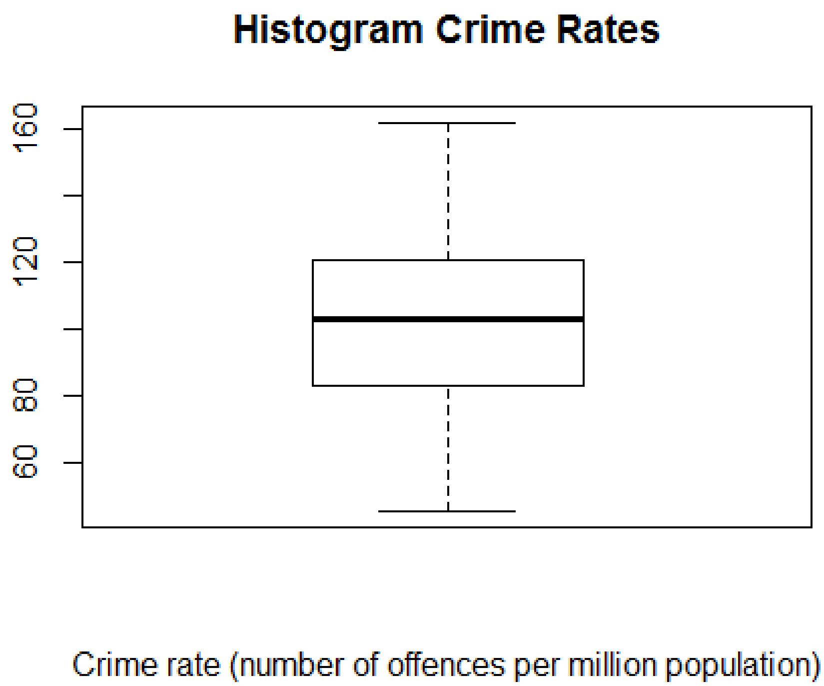
It seems there is a positive correlation between the two, i.e. when one increases the other also increases. This sort of plots is extremely useful in hypothesis testing, since it allows us to immediately figure out that some variables may be driving the variance we see in our target variable, in this case Crime rates.

Box-Plots

Box-Plots are another way to represent distributions, this time using quartiles. They are also very useful to compare distributions.

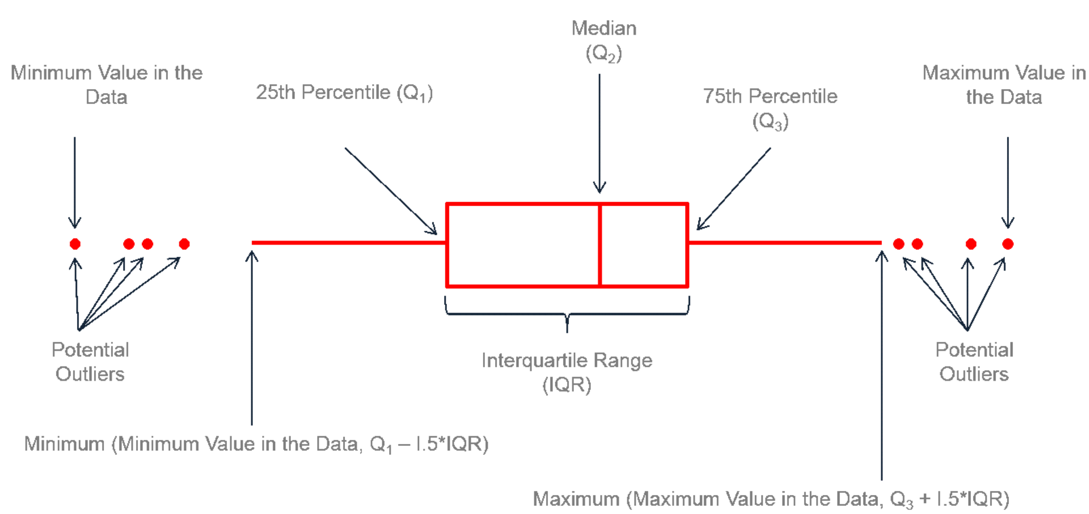
First of all, let's look at the R code to generate box-plots:

```
boxplot(Crimes$ï..CrimeRate, main="Histogram Crime Rates", xlab="Crime rate
(number of offences per million population)")
```



Box-plots are a clever way of representing distributions. They feature a box, which ranges from the first (Q1) to the third quartile (Q3), thus representing the interquartile range (measure of spread valid also for non-normal distributions). Inside there is a black line that corresponds to the median. Then we have the two whiskers, which extend up to a distance of 1.5 times the interquartile range below Q1 and above Q3. Outside this range we sometimes see dots that are considered outliers.

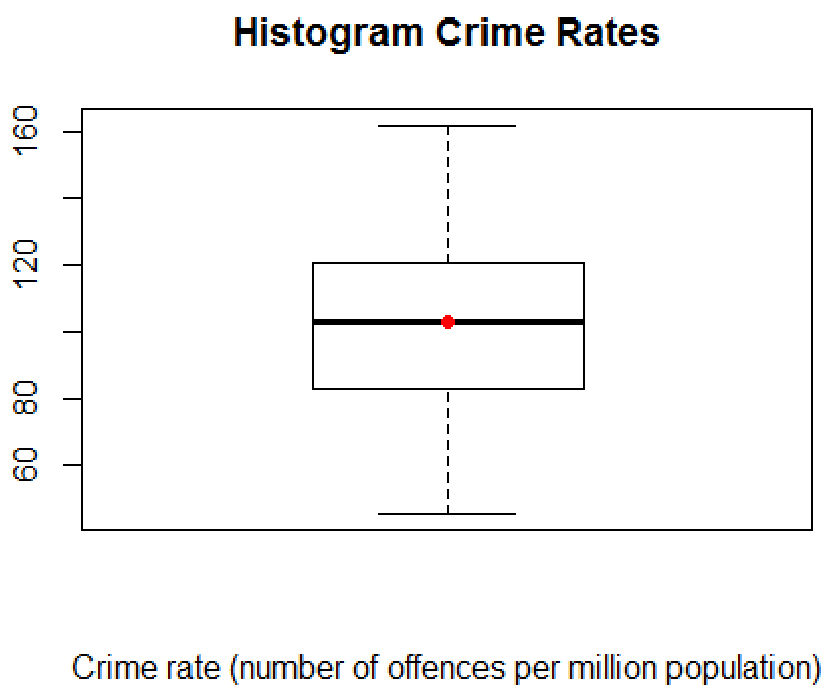
The image below illustrates how to interpret box-plots:



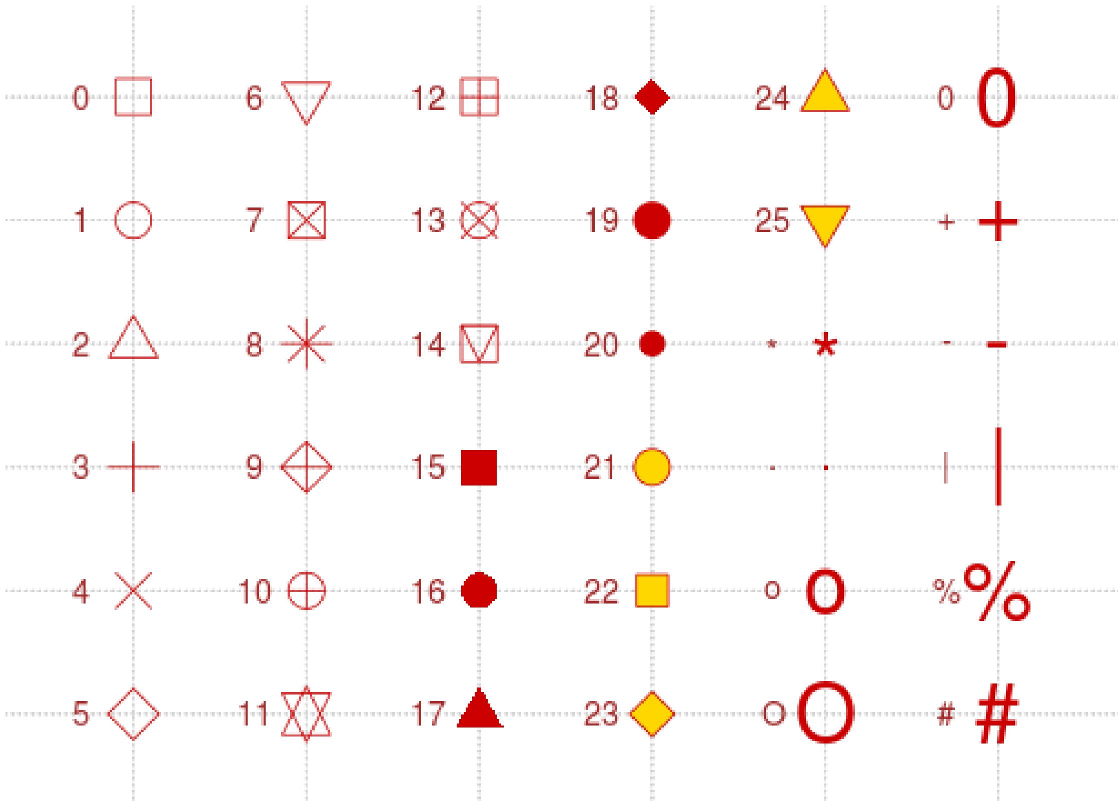
Source: lsc.studysixsigma.com

We can increase the amount of information displayed by adding a red dot on the mean value. This can be done with the function `points`:

```
boxplot(Crimes$ï..CrimeRate, main="Histogram Crime Rates", xlab="Crime rate
(number of offences per million population)")
points(mean(Crimes$ï..CrimeRate), pch=16, col="red")
```



As you can see the function `points` is written after the call to create the plot. Moreover, within the call to `points` we have two more options: `pch` and `col`. The first, `pch`, is used to change the symbol used for the dot and it can be any of the symbols below:



pch symbols, source: isu.r-forge.r-project.org

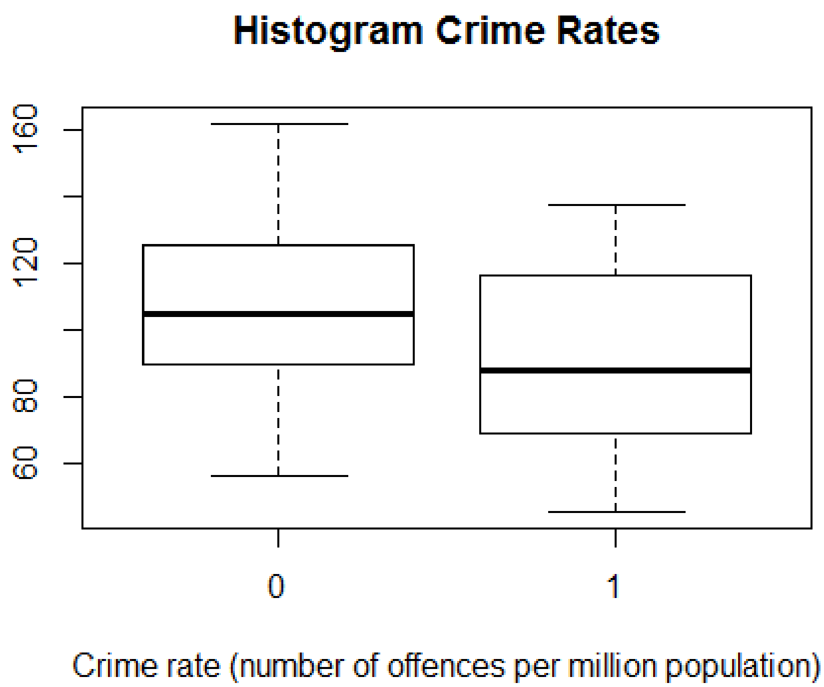
The option `col` is used to change the colour of the symbol, which by default is black. We can either write the colour: e.g. red, green, yellow. Alternatively, we can select more advanced colours from the range below:

1	white	#FFFFFF	255	255	255
2	aliceblue	#F0F8FF	240	248	255
3	antiquewhite	#FAEBD7	250	235	215
4	antiquewhite1	#FFEFDB	255	239	219
5	antiquewhite2	#EEDFCC	238	223	204
6	antiquewhite3	#CDC0B0	205	192	176
7	antiquewhite4	#8B8378	139	131	120
8	aquamarine	#7FFFD4	127	255	212
9	aquamarine1	#7FFFD4	127	255	212
10	aquamarine2	#76EEC6	118	238	198
11	aquamarine3	#66CDAA	102	205	170
12	aquamarine4	#458B74	69	139	116
13	azure	#F0FFFF	240	255	255
14	azure1	#F0FFFF	240	255	255
15	azure2	#E0EEEE	224	238	238
16	azure3	#C1CDCD	193	205	205
17	azure4	#838B8B	131	139	139
18	beige	#F5F5DC	245	245	220
19	bisque	#FFE4C4	255	228	196
20	bisque1	#FFE4C4	255	228	196
21	bisque2	#EED5B7	238	213	183
22	bisque3	#CDB79E	205	183	158
23	bisque4	#8B7D6B	139	125	107
24	black	#000000	0	0	0
25	blanchedalmond	#FFEBCD	255	235	205
26	blue	#0000FF	0	0	255
27	blue1	#0000FF	0	0	255
28	blue2	#0000EE	0	0	238
29	blue3	#0000CD	0	0	205
30	blue4	#00008B	0	0	139
31	blueviolet	#8A2BE2	138	43	226
32	brown	#A52A2A	165	42	42
33	brown1	#FF4040	255	64	64
34	brown2	#EE3B3B	238	59	59
35	brown3	#CD3333	205	51	51
36	brown4	#8B2323	139	35	35
37	burlywood	#DEB887	222	184	135
38	burlywood1	#FFD39B	255	211	155
39	burlywood2	#EEC591	238	197	145
40	burlywood3	#CDAA7D	205	170	125
41	burlywood4	#8B7355	139	115	85
42	cadetblue	#5F9EA0	95	158	160
43	cadetblue1	#98F5FF	152	245	255
44	cadetblue2	#8EE5EE	142	229	238
45	cadetblue3	#7AC5CD	122	197	205
46	cadetblue4	#53868B	83	134	139
47	chartreuse	#7FFF00	127	255	0
48	chartreuse1	#7FFF00	127	255	0
49	chartreuse2	#76EE00	118	238	0
50	chartreuse3	#66CD00	102	205	0
51	chartreuse4	#458B00	69	139	0
52	chocolate	#D2691E	210	105	30
53	chocolate1	#FF7F24	255	127	36
54	chocolate2	#EE7621	238	118	33
55	chocolate3	#CD661D	205	102	29
56	chocolate4	#8B4513	139	69	19
57	coral	#FF7F50	255	127	80
58	coral1	#FF7256	255	114	86
59	coral2	#EE6A50	238	106	80
60	coral3	#CD5B45	205	91	69
61	coral4	#8B3E2F	139	62	47
62	cornflowerblue	#6495ED	100	149	237
63	cornsilk	#FFF8DC	255	248	220
64	cornsilk1	#FFF8DC	255	248	220
65	cornsilk2	#EEE8CD	238	232	205
66	cornsilk3	#CDC8B1	205	200	177
67	cornsilk4	#8B8878	139	136	120
68	cyan	#00FFFF	0	255	255
69	cyan1	#00FFFF	0	255	255
70	cyan2	#00EEEE	0	238	238
71	cyan3	#00CDCD	0	205	205
72	cyan4	#008B8B	0	139	139
73	darkblue	#00008B	0	0	139
74	darkcyan	#008B8B	0	139	139
75	darkgoldenrod	#B8860B	184	134	11
76	darkgoldenrod1	#FFB90F	255	185	15
77	darkgoldenrod2	#EEAD0E	238	173	14
78	darkgoldenrod3	#CD950C	205	149	12
79	darkgoldenrod4	#8B6508	139	101	8
80	darkgray	#A9A9A9	169	169	169
81	darkgreen	#006400	0	100	0
82	darkgrey	#A9A9A9	169	169	169
83	darkkhaki	#BDB76B	189	183	107
84	darkmagenta	#8B008B	139	0	139
85	darkolivegreen	#556B2F	85	107	47
86	darkolivegreen1	#CAFF70	202	255	112
87	darkolivegreen2	#BCEE68	188	238	104
88	darkolivegreen3	#A2CD5A	162	205	90
89	darkolivegreen4	#6E8B3D	110	139	61
90	darkorange	#FF8C00	255	140	0
91	darkorange1	#FF7F00	255	127	0
92	darkorange2	#EE7600	238	118	0
93	darkorange3	#CD6600	205	102	0
94	darkorange4	#8B4500	139	69	0
95	darkorchid	#9932CC	153	50	204
96	darkorchid1	#BF3EFF	191	62	255
97	darkorchid2	#B23AEE	178	58	238
98	darkorchid3	#9A32CD	154	50	205
99	darkorchid4	#68228B	104	34	139
100	darkred	#8B0000	139	0	0

Author: Earl F. Glynn (2005)

Box plots are a very good way of comparing distributions of different groups. We can do that including a formula, for example specifying that we want to plot distributions of Crime Rate as a function of Youth unemployment:

```
boxplot(Crimes$ï..CrimeRate  ~ Crimes$HighYouthUnemploy, main="Histogram Crime Rates", xlab="Crime rate (number of offences per million population)")
```

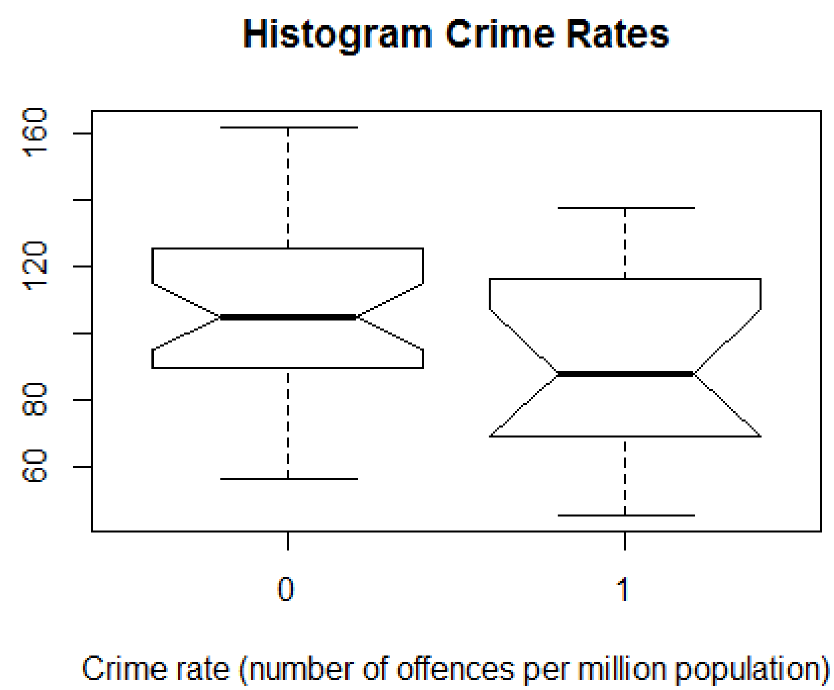


Box plots can be used with any distribution. However, their role become very important when we are dealing with non-normal data. In fact, with normal distributions we can simply use a bar-chart to plot the mean values of each group, and an error bar with the confidence interval (computed as twice the standard error of the mean). However, for data that do not fit a normal distribution this is not possible and this is where box plot become very useful. In fact, using the interquartile range (`IQR`) we can compute confidence intervals around the median, with the following equation:

$$CI_{Median} = Median \pm 1.57 \times \frac{IQR}{\sqrt{n}}$$

Confidence intervals around the median can be plotted in R as notches, with the option `notch`:

```
boxplot(Crimes$ï..CrimeRate  ~ Crimes$HighYouthUnemploy, notch=T, main="Histogram Crime Rates", xlab="Crime rate (number of offences per million population)")
```



The interpretation is very similar to the confidence intervals around the mean. If the two notches are overlapping there are good chances that with a formal test the two groups will not result statistically different.

Conclusions

In this lecture we learned the basics of the R language, such as importing and subsetting data. We also started learning useful technique to explore our dataset, both in terms of descriptive indexes, and by visualising our variables.

References

Material to implement what we discussed during lectures can be downloaded from my OneDrive.

I also developed a video tutorial for Pack Publishing, which again students can download from OneDrive:

OneDrive

Homework

Homework are meant to help you during the learning process. They will not be marked and they are not mandatory. However, if you have time and you want to do some additional work to better understand the R language these are some things you can try. Please save all your homework, from each day, into a single file: name_surname_StudentID.R

Please identify each day with specific comments. A comment in R can be included with the hash-tag (#):

```
#Comment: you can write whatever neccesary for me to understand your reasoning
```

At the end of the module you can send the R file to me: fveronesi@harper-adams.ac.uk

You can find the list of homework below:

1. From this page, download the Diet dataset and place it in a folder of your choice. Then set the working directory pointing to the same folder where you downloaded the dataset. Finally load the dataset using `read.csv`.
2. Subset the dataset by gender (be careful for the NA values) and compute the mean values for the variable `weight6weeks` for both subsets.
3. Create a bar-chart using the two subsets.
4. Create a scatterplot between `pre.weight` and `weight6weeks`.
5. Comment the scatterplot and the relation between variables.