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2-1. EXPLORATORY DATA ANALYSIS IN R

2-1.1 Basic concepts of descriptive data analysis

Data matrix structure (data.frame in R)

POPULATION

	Carac1	Carac2	...
Individual 1	value	value'	...
Individual 2	value''	value'''	...
.			
.			

Sample: Subset of a population

Features \equiv Variables

Values : numeric or alphanumeric

Example 2.1: Age data and residence's place of students of a UPC's class

	edad	residencia	llista.ED	llista.ED_1
1	19	BCN-AMB	22	22
2	20	BCN-AMB	25	25
3	19	BCN-AMB	34	34
4	20	BCN-AMB	35	35
5	19	BCN-AMB	41	41
6	19	BCN-AMB	41	41
7	9	BCN-AMB	46	46
8	20	BCN-AMB	46	46
9	19	BCN-AMB	46	46
10	19	BCN-AMB	47	47
11	19	Resta Catalunya	49	49
12	19	Resta Catalunya	54	54
13	23	Resta Catalunya	54	54
14	19	Estat Espanyol	59	59
15	19	Estat Espanyol	60	60
16	NA	<NA>	NA	100

2-1 EXPLORATORY DATA ANALYSIS IN R

2-1.2 Typology of variables

Numerical (continuous)

Continuous (reals values or simply many different values)

Ex: Incomes, weight, lung capacity, etc.

COVARIATES/
COVARIANTS

Discretes (equivalent to whole numbers or natural ... if there are many values) continuous)

Ex: Children's number, age, etc.

Categorical (qualitatives)

(values : modalities or categories)

With order (ordinal)

Ex: Level of education, Labor category, etc.

Unordered (nominal)

Ex: Gender, Race, Marital status ...

FACTORS

Categorical variables come pruned expressed by a numerical value (Ex. Gender: Man = 0, Woman = 1).
(Not to be confused with quantitative variables)

2-1 EXPLORATORY DATA ANALYSIS IN R

2-1.3 Statistical Prediction Models

- Interest: explain one (or more) response variable or dependent.
- From explanatory variables or predictors.

Classification of variables:

- Pure nominal or categorical variables: binary (dichotomous) if they have 2 categories and polytomous if they have more than 2 categories. The categories do not have any semantics associated order. They are qualitative variables.
- Ordinal Variables. They are categorical variables with notion of order among the categories, usually more than 2. *They often come from the discretization of continuous variables* or are discrete a.v.. They are qualitative variables.
- Continuous or quantitative variables. Theoretically associated with continuous measures.
- Factor: qualitative variable explanatory. The different categories are called levels.
- Covariant: continuous explanatory variable.

2-1 EXPLORATORY DATA ANALYSIS IN R

2-1.4 Univariate descriptive analysis

Continuous variable description: *Missing* and *Outliers*

- Numerical values

- Measures of Central Tendency: *Mean, Median, Mode*
- Measures of Dispersion: *Variance, Standard Deviation, Quartiles, IQR, Maximum, Minimum.*

- Graph Representations

- Histogram, Cumulative Histogram. Absolute or relative.
- *BoxPlot.*

Description of a categorical variable: Graph Representations

- Bar chart: absolute or relative.
- *Pie Chart.*

2-1 EXPLORATORY DATA ANALYSIS IN R

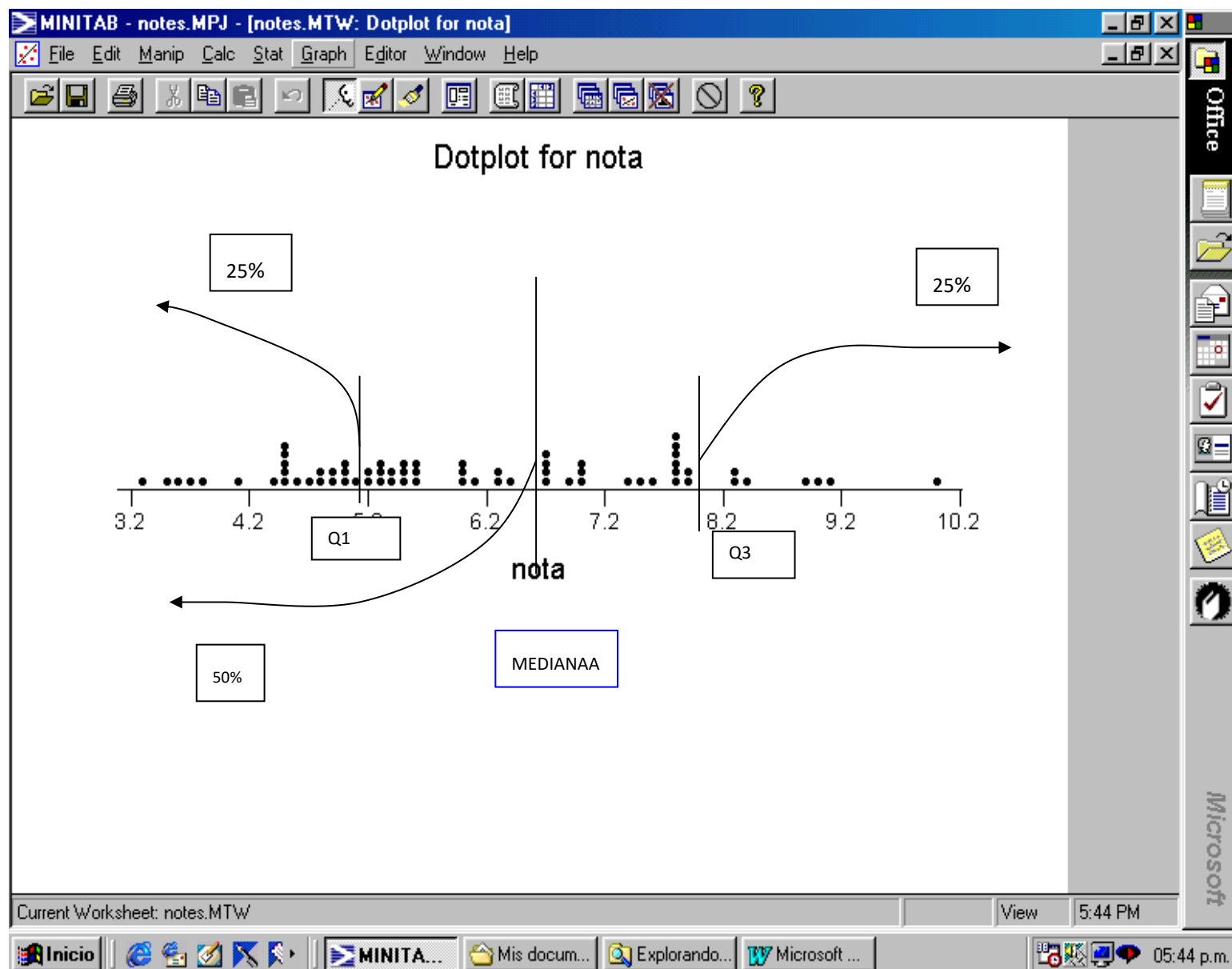
2-1.4.1 Continuous Univariate Analysis Description: Numeric Indicators

```
> summary(dataframe)
```

- Mean $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$
- Median: Value of the *variable* such that
50% Observations are < Median (Q2) & 50% Observations are > Median (Q2)
- Quartile Q1 of the 25% and quartile Q3 of the 75%: Values of the variable that

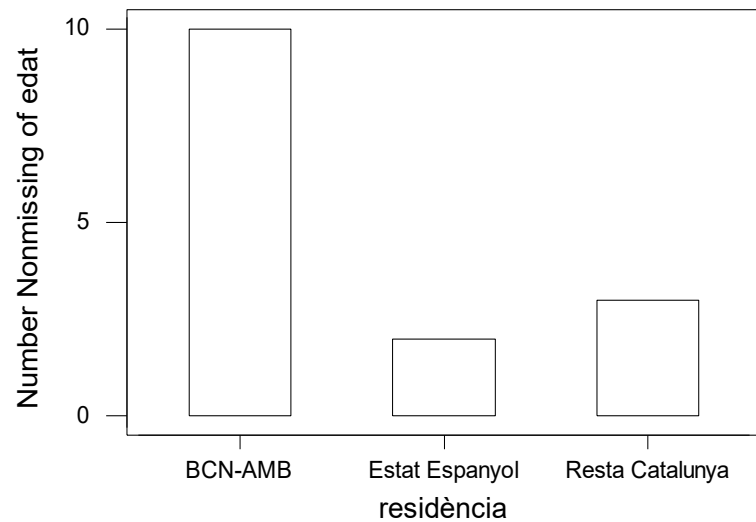
<i>25% Observations are < Q1</i>	&	<i>75% Observations are > Q1</i>
<i>75% Observations are < Q3</i>	&	<i>25% Observations are > Q3</i>
- Variance $s_x^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2$
- Standard Deviation s_x

2-1 EXPLORATORY DATA ANALYSIS IN R

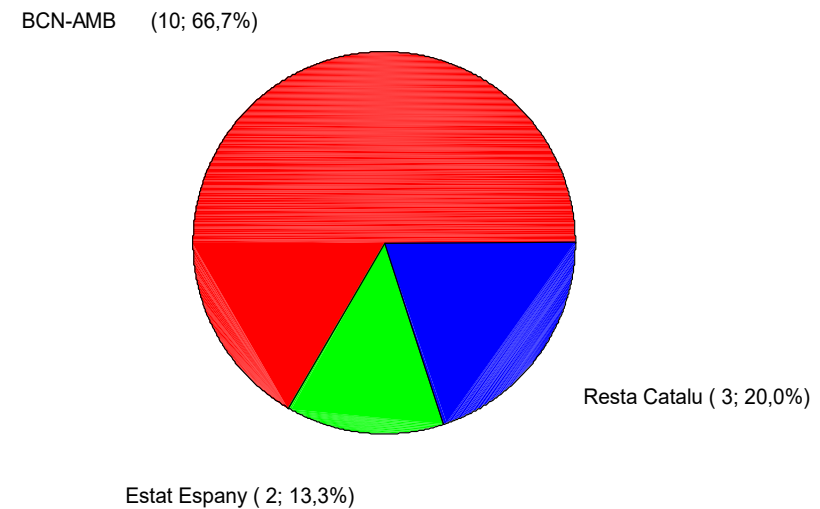


2-1 EXPLORATORY DATA ANALYSIS IN R

2-1.4.2 Univariate Analysis Description categorical



Pie Chart of residència



Bar chart (absolute or relative)

`barplot(table())` in R

Pie Chart

2-1 EXPLORATORY DATA ANALYSIS IN R

```
> tema2.1 <- read.table("tema2.1.txt",header=T,sep='\t',na.string='')
> tema2.1
```

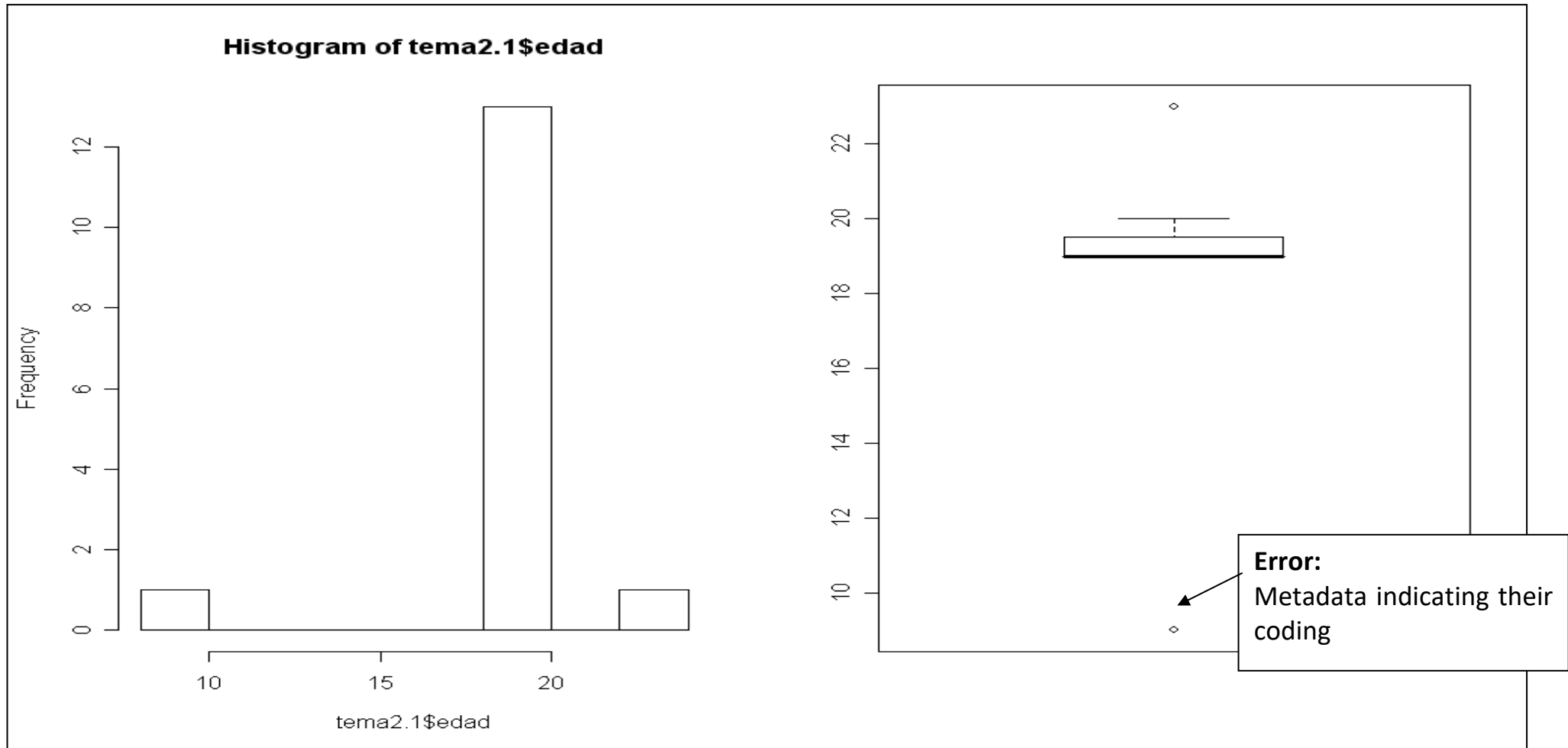
	edad	residencia	llista.ED	llista.ED_1
1	19	BCN-AMB	22	22
2	20	BCN-AMB	25	25
3	19	BCN-AMB	34	34
4	20	BCN-AMB	35	35
5	19	BCN-AMB	41	41
6	19	BCN-AMB	41	41
7	9	BCN-AMB	46	46
8	20	BCN-AMB	46	46
9	19	BCN-AMB	46	46
10	19	BCN-AMB	47	47
11	19	Resta Catalunya	49	49
12	19	Resta Catalunya	54	54
13	23	Resta Catalunya	54	54
14	19	Estat Espanyol	59	59
15	19	Estat Espanyol	60	60
16	NA	<NA>	NA	100

```
> summary(tema2.1)
```

	edad	residencia	llista.ED	llista.ED_1
Min.	: 9.0	BCN-AMB	:10	Min. : 22.00
1st Qu.:	19.0	Estat Espanyol	: 2	1st Qu.: 38.00
Median	:19.0	Resta Catalunya:	3	Median : 46.00
Mean	:18.8	NA's	: 1	Mean : 47.44
3rd Qu.:	19.5			3rd Qu.: 51.50
Max.	:23.0			Max. : 60.00
NA's	: 1.0			Max. :100.00

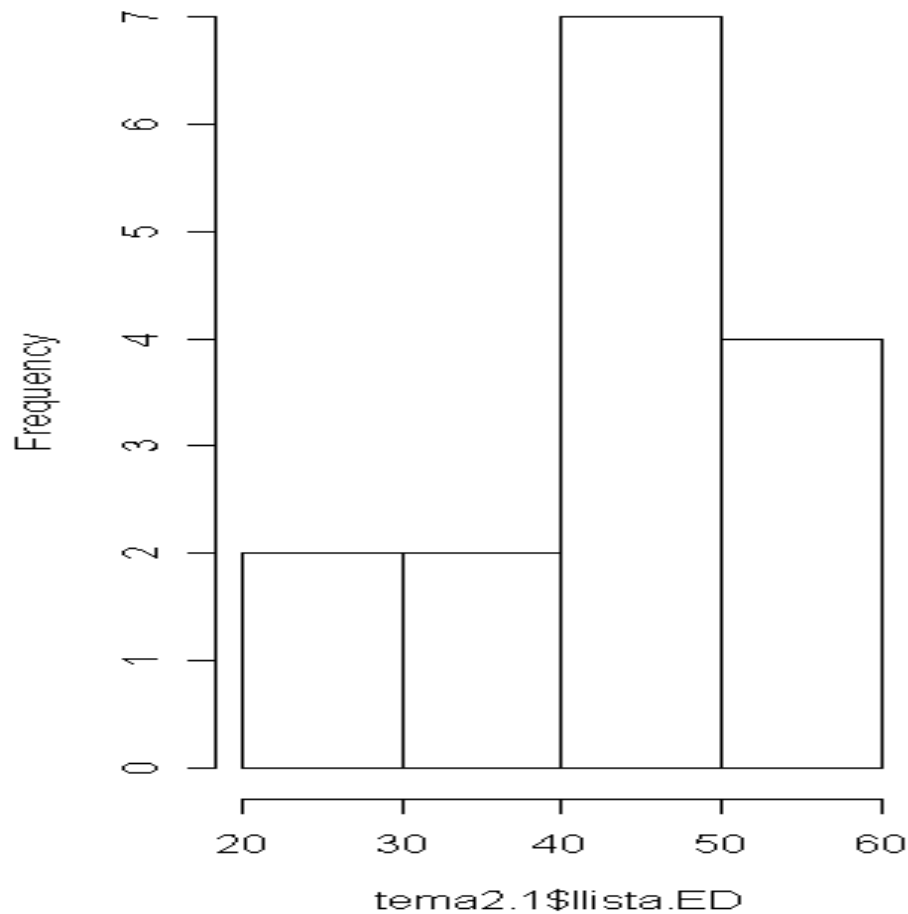
2-1 EXPLORATORY DATA ANALYSIS IN R

```
par(mfrow=c(1,2))  
hist(tema2.1$edad)  
boxplot(tema2.1$edad)
```

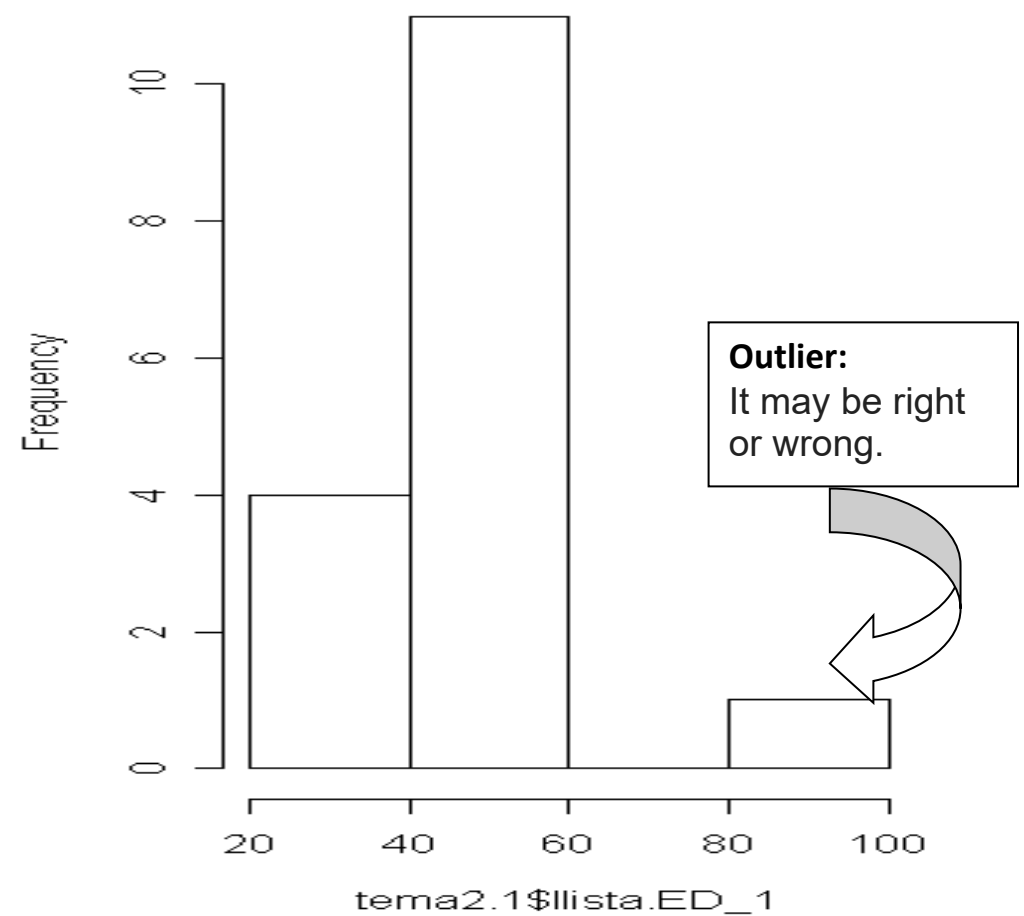


2-1 EXPLORATORY DATA ANALYSIS IN R

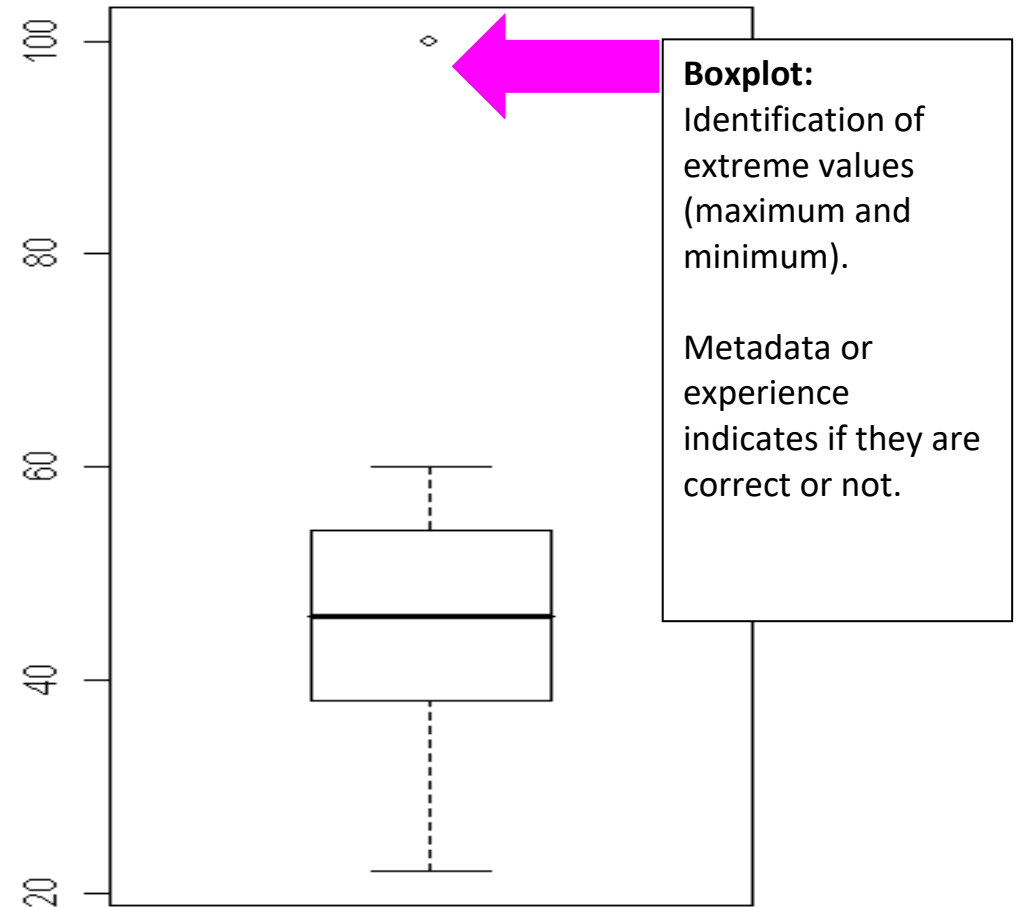
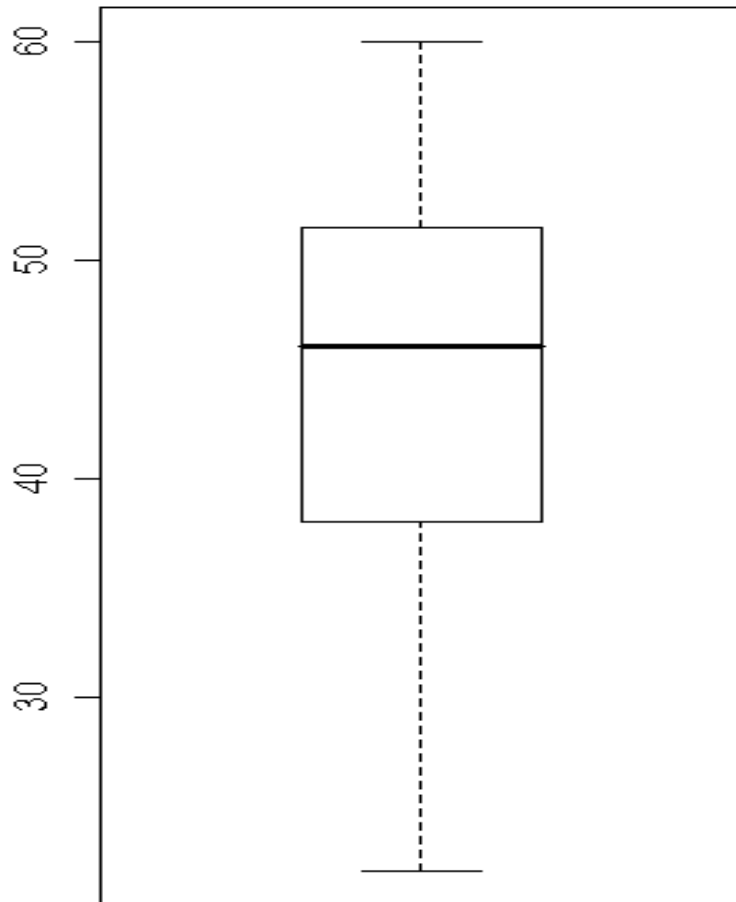
Histogram of tema2.1\$llista.ED



Histogram of tema2.1\$llista.ED_1



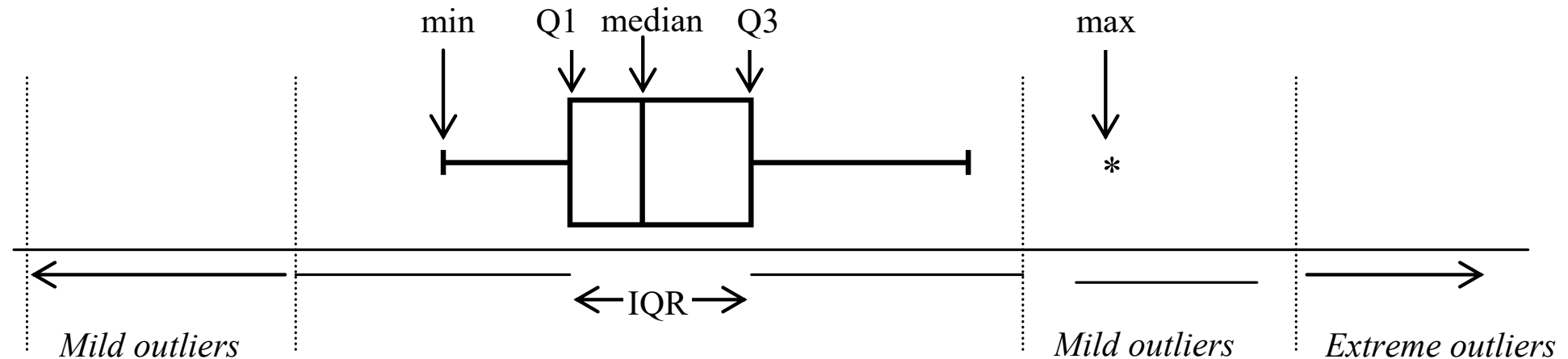
2-1 EXPLORATORY DATA ANALYSIS IN R



2-1 EXPLORATORY DATA ANALYSIS IN R

2-1.5 Box-plot

“Five issues Summary” (Min, Q1, Me, Q3, Max) for Univariate DE to detect the existence of outliers.



The area between Q3 and $Q3 + 1.5 \text{ IQR}$ and $Q3 + 3 \text{ IQR}$ is called mild outliers upper zone. Similarly with the lower tail: between $Q1 - 1.5 \text{ IQR}$ and $Q1 - 3 \text{ IQR}$. The area above the point $Q3 + 3 \text{ IQR}$ area called extreme outliers. As a general rule, it isn't worrying to see up to 1% of extreme outliers and up to 5% of mild outliers in any distribution.

2-1 EXPLORATORY DATA ANALYSIS IN R

2-1.6 Bivariate descriptive analysis

Study of the relationship between variables in pairs. Naturally, is the simplest case of multivariate descriptive analysis, that globally study the relationships among a set of variables that can be very large (more complex techniques that connect directly with Data Mining).

The most common techniques of bivariate descriptive analysis, as happened in the univariate case, are of two types:

- Graph: Allow display as the relationship between two variables.
- Numeric: Quantify what you see on the graph with a appropriate statistic.

The nature of the variables to study plays a key role in determining the tools to use in each case. Three cases are distinguished primarily:

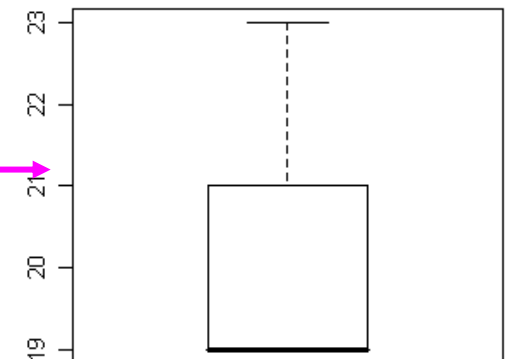
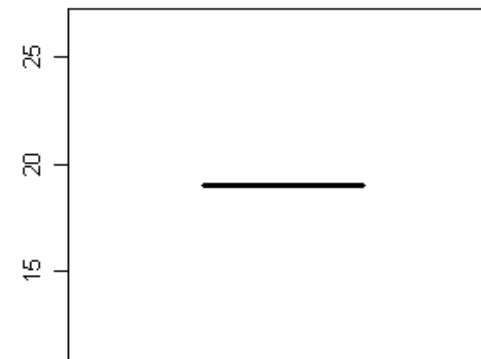
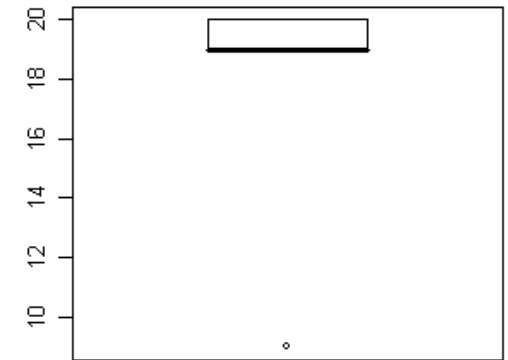
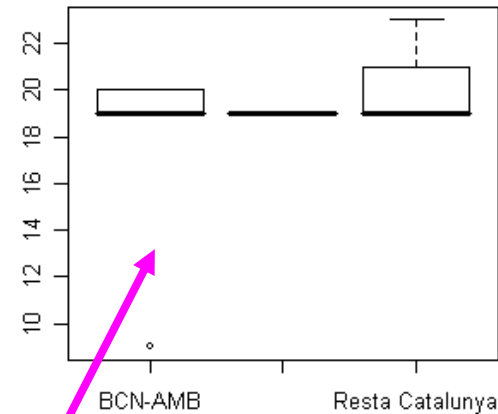
- Relationships between a numeric variable and a categorical. For example, descriptive groups.
- Relationships between two categorical variables. For example, contingency tables.
- Relationships between two quantitative variables. For example, simple linear regression.

2-1 EXPLORATORY DATA ANALYSIS IN R

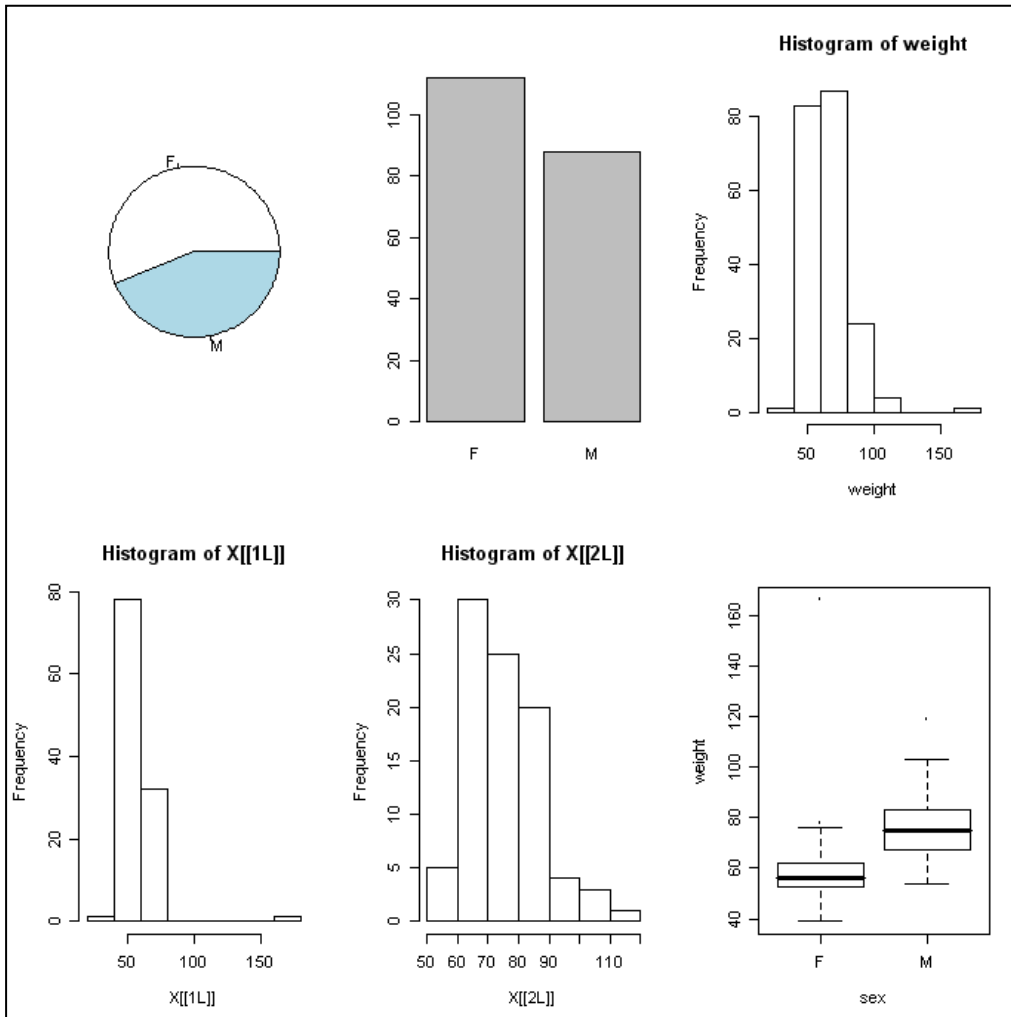
In example you can try a descriptive groups, consider age as a response variable and place of residence as the explanatory variable.

```
# AD Bivariant per grups
> tapply(tema2.1$edad, tema2.1$residencia, mean)
BCN-AMB      Estat Espanyol  Resta Catalunya
18.30000      19.00000      20.33333

tapply(tema2.1$edad, tema2.1$residencia, summary)
"BCN-AMB"
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  9.00  19.00   19.00   18.30  19.75   20.00
"Estat Espanyol"
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
   19    19    19      19    19      19
"Resta Catalunya"
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
19.00  19.00   19.00   20.33  21.00   23.00
> attach(tema2.1)
> par(mfrow=c(2,2))
> plot(edad~residencia, data=tema2.1)
>
> apply(tema2.1$edad, tema2.1$residencia, boxplot)
```



2-1 EXPLORATORY DATA ANALYSIS IN R – BIVARIATE: NUMERIC VS FACTOR



```

par(mfrow=c(2,3))
attach(Davis)
pie( table( sex ))
barplot( table(sex) )
hist( weight )

```

```

tapply( weight, sex, hist )# Not nice
plot( weight ~ sex ) # Boxplot is
default plot

```

2-2. EDA IN R – BIVARIATE: 2 NUMERICS Y VS X

2-2.1 Numeric statistics to assess linear relationship between Y and X

Covariance, $COV(y,x)=COV(x,y)$, defined as $E(YX) - E(X)E(Y)$

- Disadvantage: Depends on units, so not direct interpretation

Pearson's coefficient of correlation, suitable for assessment in normal data

$$\rho(X,Y) = \frac{Cov(X,Y)}{\sigma_X \sigma_Y} \quad \text{and} \quad \sigma_X = \sqrt{Var(X)} \quad \sigma_Y = \sqrt{Var(Y)}$$

- Advantage: Adimensional, no affected by units
 - $\rho(X, Y)$ **range is** $[-1, 1]$.
 - $\rho(X, Y) > 0$ means positive relationship X and Y.
 - $\rho(X, Y) < 0$ means negative relationship X and Y,.
 - $\rho(X, Y) = 0$ indicates uncorrelated variables, not equivalent to independence.
 - If $Y = aX + b$ then $|\rho(X, Y)| = 1$.
- **Spearman's coefficient of correlation**, is a nonparametric measure of statistical dependence.

2-3. EDA IN R – BIVARIATE: 2 NUMERICS Y VS X

In R, use `var(Davis[,2:3])` or try with Census Data `data("CPS1985")` in library AER.

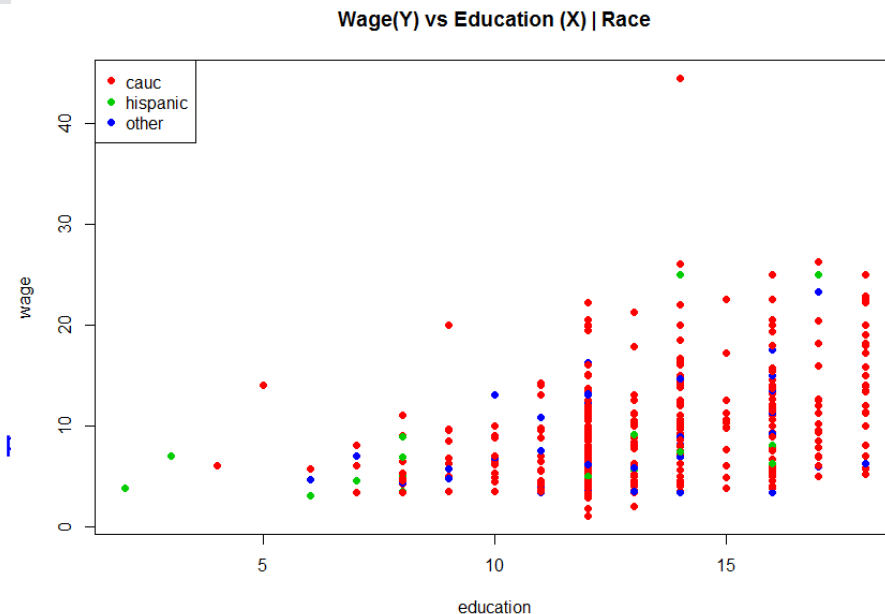
```
> library(AER)
> data("CPS1985")
> df<-CPS1985
> ls()
[1] "CPS1985" "df"
> dim(df) # dimensions: rows and columns
[1] 534 11
> summary(df)
```

wage	education	experience	age	ethnicity	region	gender	occupation
Min. : 1.000	Min. : 2.00	Min. : 0.00	Min. :18.00	cauc :440	south:156	male :289	worker :156
1st Qu.: 5.250	1st Qu.:12.00	1st Qu.: 8.00	1st Qu.:28.00	hispanic: 27	other:378	female:245	technical :105
Median : 7.780	Median :12.00	Median :15.00	Median :35.00	other : 67			services : 83
Mean : 9.024	Mean :13.02	Mean :17.82	Mean :36.83				office : 97
3rd Qu.:11.250	3rd Qu.:15.00	3rd Qu.:26.00	3rd Qu.:44.00				sales : 38
Max. :44.500	Max. :18.00	Max. :55.00	Max. :64.00				

```
> attach(df)
> # Bivariate analysis: 2 numeric variables
> plot(education,wage,col=as.numeric(ethnicity)+1,
      main="Wage(Y) vs Education (X) | Race",pch=19)
> legend("topleft",legend=levels(ethnicity),col=2:4,
      pch=19)
> cor(wage,education,method="spearman")
[1] 0.3813425
> cor(wage,education,method="pearson") # The one defined in R
[1] 0.3819221
```

Nicer option: `scatterplot`, try in lab session

```
> library(car)
> scatterplot(wage~education|ethnicity,main="Wage(Y) vs Education (X) | Race",smooth=FALSE)
```



2-4. EDA IN R – BIVARIATE: 2 FACTORS, A AND B

2-4.1 Numeric statistics to assess linear relationship A and B

Non-existent. Analysis of Contingency Tables and classical inference test to assess Independence of both factors using Chi-Squared Test: `chisq.test()` in R, arguments a contingency table.

```
> ta<-table(ethnicity,sector)
```

```
> ta
```

	sector		
ethnicity	manufacturing	construction	other
cauc	81	21	338
hispanic	4	0	23
other	14	3	50

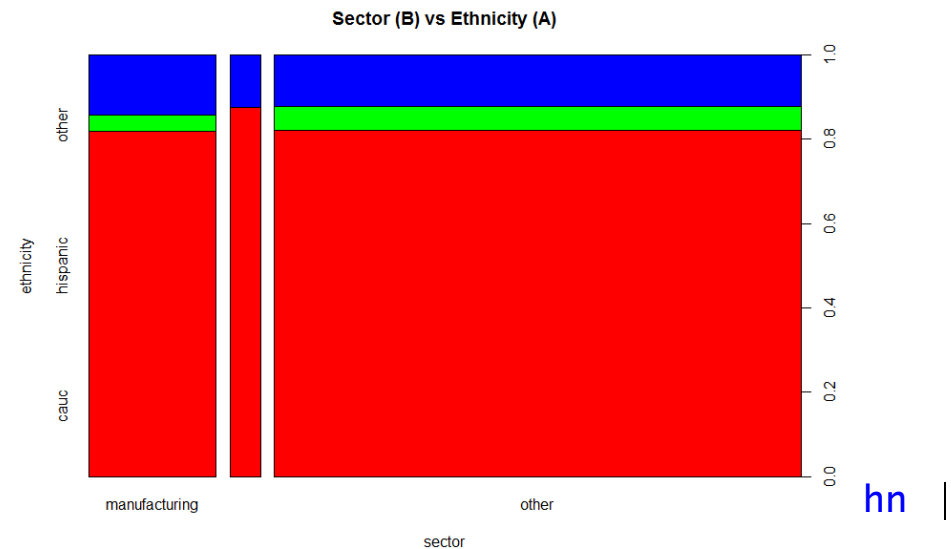
```
> round(prop.table(ta,2),2)
```

	sector		
ethnicity	manufacturing	construction	other
cauc	0.82	0.88	0.82
hispanic	0.04	0.00	0.06
other	0.14	0.12	0.12

```
> plot(ethnicity~sector,main="Sector (B) vs Ethnicity (A)",col=rainbow(3))
> chisq.test(ta)
```

```
Pearson's Chi-squared test data: ta
X-squared = 1.9819, df = 4, p-value = 0.7391
```

Warning message: In `chisq.test(ta)` : Chi-squared approximation may be incorrect



EDA IN R – BIVARIATE: 2 FACTORS, A AND B

Graphic display (default in R): mosaic plot

More than 2 dimensions: use `xtabs()` command in R

```
> xtabs(~gender+ethnicity+sector)
, , sector = manufacturing
```

	ethnicity		
gender	cauc	hispanic	other
male	48	2	10
female	33	2	4

```
, , sector = construction
```

	ethnicity		
gender	cauc	hispanic	other
male	19	0	3
female	2	0	0

```
, , sector = other
```

	ethnicity		
gender	cauc	hispanic	other
male	169	12	26
female	169	11	24

```
> ta<-xtabs(~gender+ethnicity+sector)
> chisq.test(ta)
```

Chi-squared test for given probabilities

```
data: ta
X-squared = 1573.753, df = 17, p-value < 2.2e-16
```