

Exploratory Data Analysis II and Plots with R

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1. Definition
2. Types of correlation (Pearson, Spearman)

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1. Elegant graphics for data analysis

- R is a powerful tool to plot your data
- Hadley Wickam (2009) introduced a modern (and perhaps easier) way to plot your data
- Extensions to ggplot2
 - GGally, ggrepel, ...

Hadley Wickam book

<http://moderngraphics11.pbworks.com/f/ggplot2-Book09hWickham.pdf>

<https://ggplot2-book.org/>

STHDA (Statistical tools for high-throughput data analysis)

<http://www.sthda.com/english/wiki/ggplot2-essentials>

R Colors

<http://www.stat.columbia.edu/~tzheng/files/Rcolor.pdf>

1. Elegant graphics for data analysis

How ggplot2 works?

- It is based on the *Grammar of Graphics* (Wilkinson 2005)
- Grammar tells us that a graphic maps the data to the aesthetic attributes (colour, shape, size) of geometric objects (points, lines, bars).
- Plot may also include statistical transformations of the data and information about plot's coordinate system

1. Elegant graphics for data analysis

- Mapping components:
 - **Layer:** Geoms (what you actually see in the plot: points, lines,...), stats (summarise the data)
 - **Scales:** how we want to see the data (aesthetic). Color, shapes, legend, axes....
 - **Coord:** axes, gridlines
 - **Facet:** if you want to divide your data in different plots
 - **Theme:** Font size, background colors, ...

1. Elegant graphics for data analysis

- How to install: `install.packages("ggplot2")`
- First steps. Three key components:
 - Data
 - Aesthetic mappings between variables
 - A least one **layer**. Usually created with a **geom** function

1. Elegant graphics for data analysis

- The data: (<https://ggplot2.tidyverse.org/reference/mpg.html>)
`head(mpg)`

```
# A tibble: 6 x 11
  manufacturer model displ  year   cyl trans      drv   cty   hwy fl      class
  <chr>         <chr> <dbl> <int> <int> <chr>   <chr> <int> <int> <chr> <chr>
1 audi         a4      1.8  1999     4 auto(l5) f     18    29 p     compact
2 audi         a4      1.8  1999     4 manual(m5) f     21    29 p     compact
3 audi         a4      2    2008     4 manual(m6) f     20    31 p     compact
4 audi         a4      2    2008     4 auto(av)   f     21    30 p     compact
5 audi         a4      2.8  1999     6 auto(l5)   f     16    26 p     compact
6 audi         a4      2.8  1999     6 manual(m5) f     18    26 p     compact
```

A data frame with 234 rows and 11 variables:

manufacturer: manufacturer name

model: model name

displ: engine displacement, in litres

year: year of manufacture

"type" of car

cyl: number of cylinders

trans: type of transmission

drv: the type of drive train, where f = front-wheel drive, r = rear wheel drive, 4 = 4wd

cty: city miles per gallon

hwy: highway miles per gallon

fl: fuel type

class

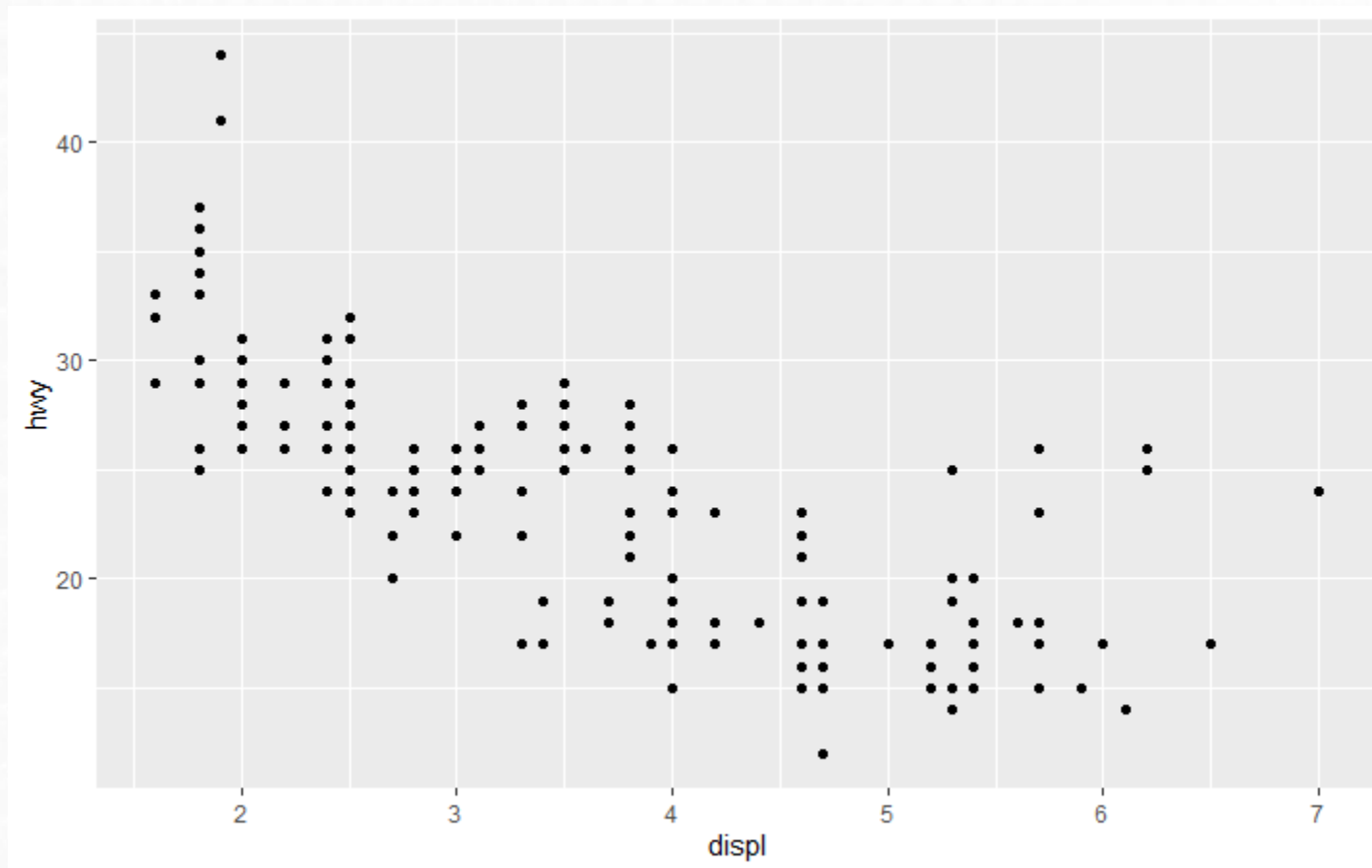
1. Elegant graphics for data analysis

- The plot:

```
ggplot(mpg, aes(x = displ, y = hwy)) +  
  geom_point()
```

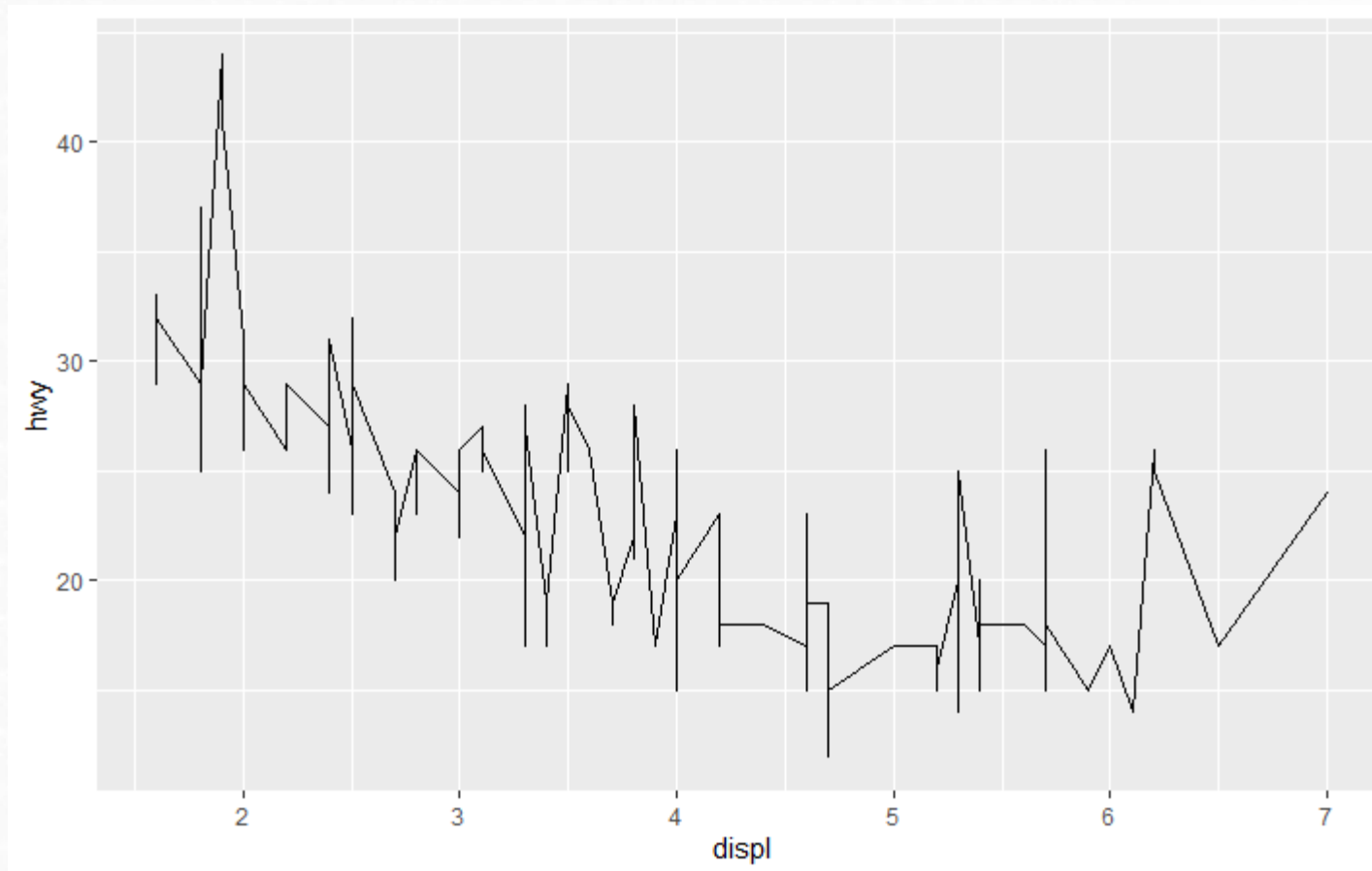
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```
ggplot(mpg, aes(x = displ, y = hwy)) +  
  geom_point()
```



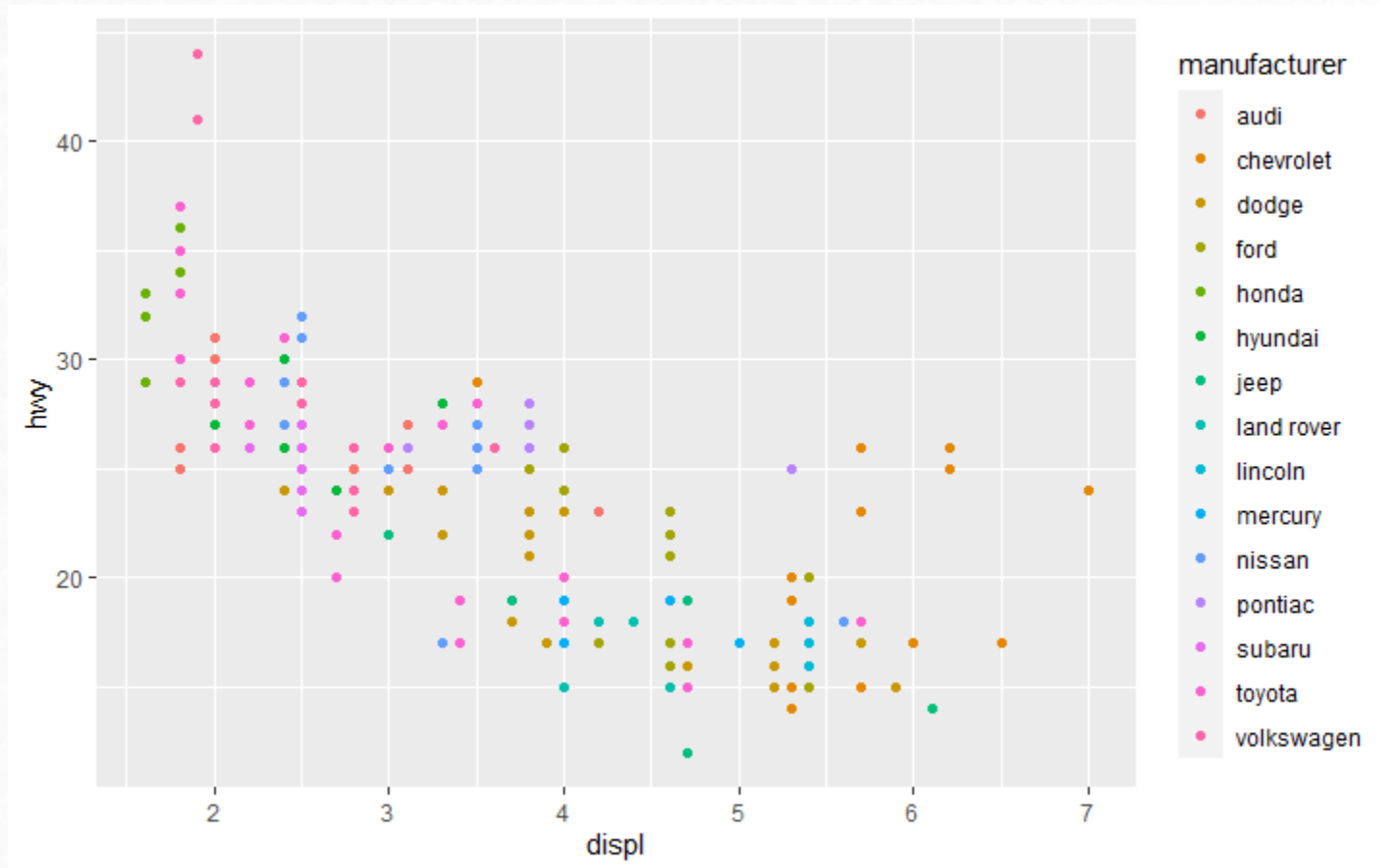
1. Elegant graphics for data analysis

```
ggplot(mpg, aes(x = displ, y = hwy)) +  
  geom_line()
```



1. Elegant graphics for data analysis

```
ggplot(mpg, aes(x = displ, y = hwy, color = manufacturer)) +  
  geom_point()
```



1. Elegant graphics for data analysis

```
ggplot(mpg, aes(x = displ, y = hwy, color = manufacturer, shape = drv)) +  
  geom_point()
```

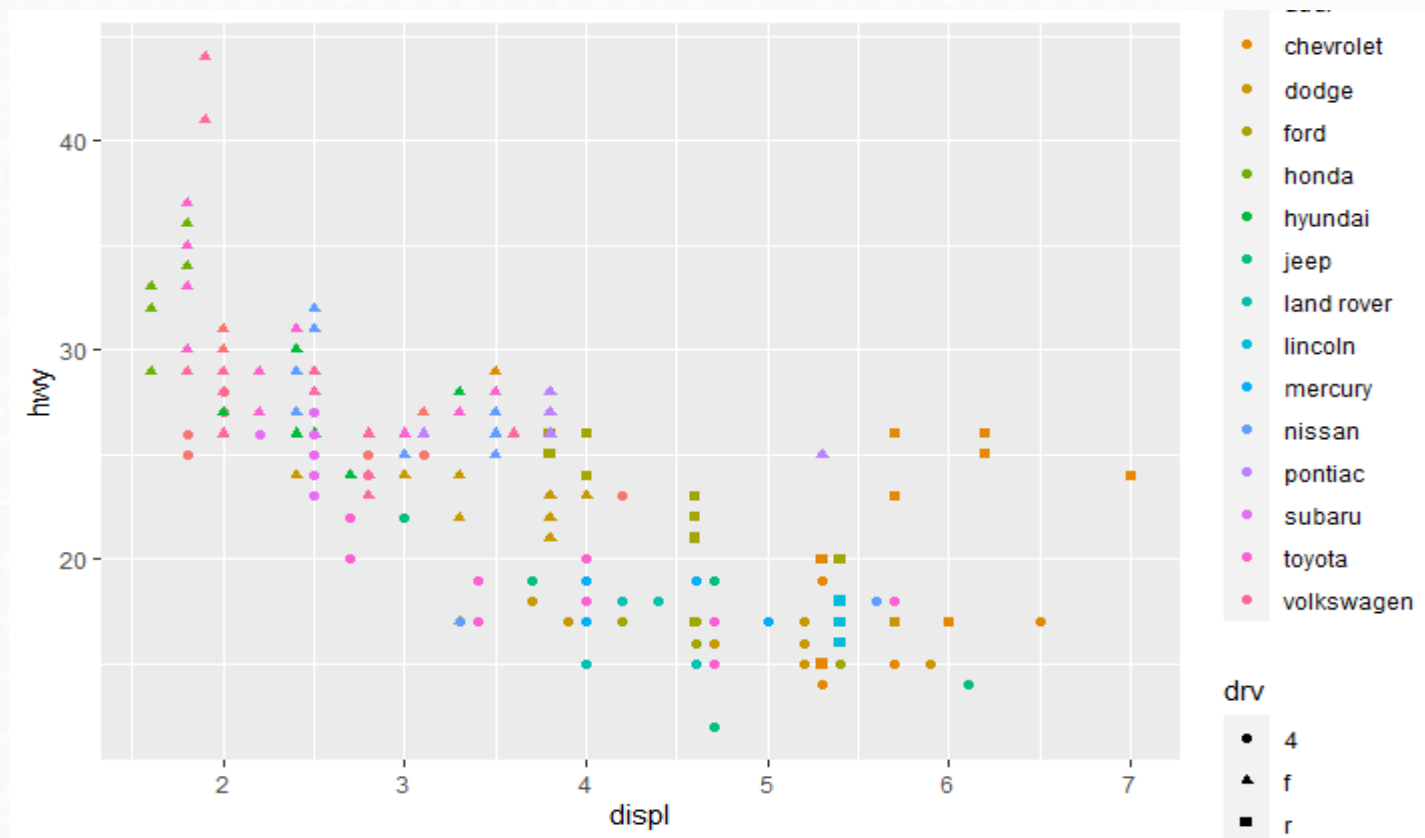


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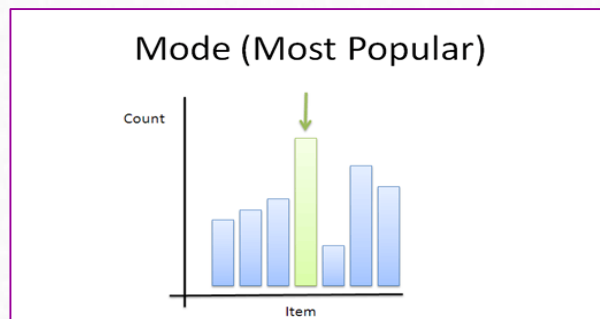
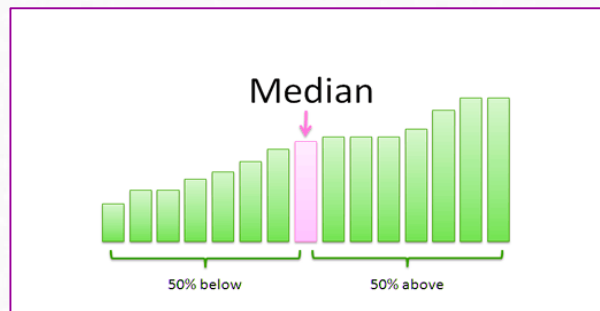
2. From univariate to Bivariate analysis

Last week we learned...

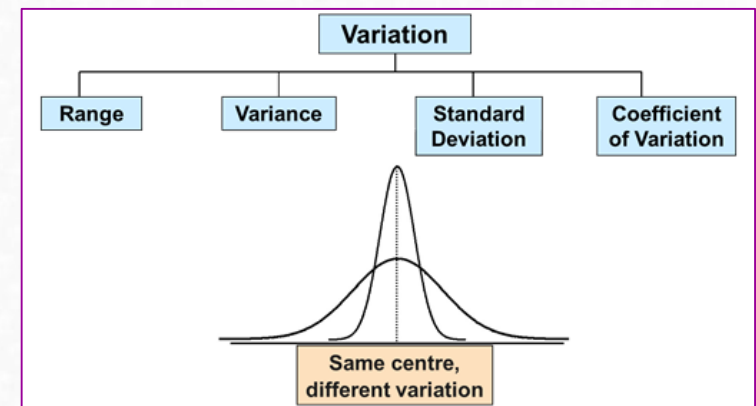
- We can analyse and describe each variable one by one:

1. With some measures:

Measures of central tendency

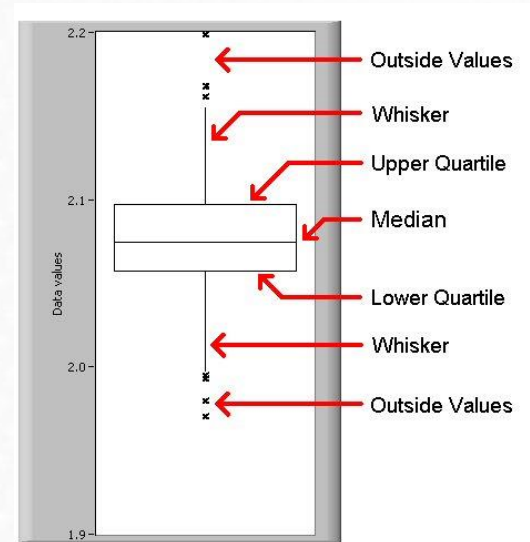
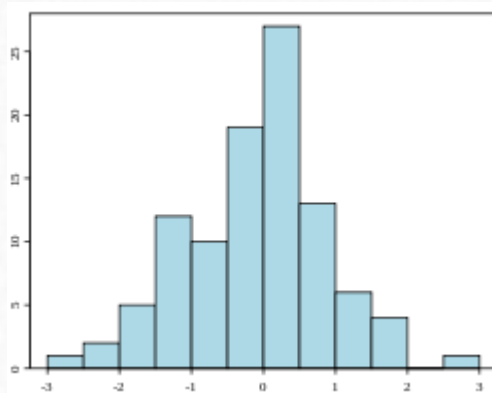


Measures of dispersion



2. From univariate to Bivariate analysis

2. Some graphics



Days	Number of Red-Boxes Sold
Monday	4
Tuesday	2
Wednesday	3
Thursday	5
Friday	8
Saturday	1

2. From univariate to Bivariate analysis

- In univariate analysis **only one** variable is analyzed each time



the purpose of the analysis is **descriptive**

- If there are more than one variable in the dataset it could be interesting to guess if:
 - Does exist a relation between the two variables?
 - How important is this relation?
 - Which is the direction of the relation?

2. From univariate to Bivariate analysis

	registro	area	f_nac	edad	grupedad	peso	talla	bua	imc	clasific	me
1	3	10	11659420800	57	55 - 59	70.0	168.0	69	24.80159	OSTEOPENIA	
2	4	10	11671689600	46	45 - 49	53.0	152.0	73	22.93975	OSTEOPENIA	
3	10	10	11721024000	45	45 - 49	64.0	158.0	81	25.63692	NORMAL	
4	11	10	11464416000	53	50 - 54	78.0	161.0	58	30.09143	OSTEOPENIA	
5	12	10	11690784000	46	45 - 49	56.0	157.0	89	22.71897	NORMAL	
6	15	10	11716012800	45	45 - 49	63.5	170.0	76	21.97232	NORMAL	
7	16	10	11623737600	48	45 - 49	86.0	161.0	87	33.17773	NORMAL	
8	17	10	11562307200	50	50 - 54	61.5	164.0	74	22.86585	NORMAL	
9	18	10	11538028800	51	50 - 54	60.5	158.0	58	24.23490	OSTEOPENIA	
10	20	10	11332483200	57	55 - 59	64.0	149.0	61	28.82753	OSTEOPENIA	
11	21	10	11631945600	48	45 - 49	70.3	160.0	67	27.46094	OSTEOPENIA	
12	22	10	11425536000	55	55 - 59	74.4	160.0	68	29.06250	OSTEOPENIA	
13	23	10	11553235200	50	50 - 54	55.5	154.5	73	23.25070	OSTEOPENIA	
14	24	10	11367302400	56	55 - 59	89.0	166.0	61	32.29787	OSTEOPENIA	
15	25	10	11585635200	49	45 - 49	50.6	157.0	68	20.52822	OSTEOPENIA	
16	26	10	11572156800	50	50 - 54	71.4	152.0	74	30.90374	NORMAL	
17	27	10	11590992000	49	45 - 49	78.0	157.0	62	31.64429	OSTEOPENIA	
18	28	10	11293516800	58	55 - 59	72.0	162.0	65	27.43484	OSTEOPENIA	
19	29	10	11215238400	61	60 - 64	68.0	155.5	65	28.12212	OSTEOPENIA	
20	30	10	11405664000	55	55 - 59	75.0	161.0	92	28.93407	NORMAL	
21	31	10	11633155200	48	45 - 49	66.5	153.0	11	28.40788	OSTEOPOROSIS	
22	32	10	11287728000	59	55 - 59	101.0	156.0	82	41.50230	NORMAL	
23	34	10	10992758400	68	65 - 69	66.5	145.0	57	31.62901	OSTEOPENIA	
24	35	10	10909382400	69	65 - 69	70.0	168.0	48	24.80159	OSTEOPOROSIS	
25	36	10	11643868800	48	45 - 49	60.1	153.0	86	25.67389	NORMAL	
26	37	10	11551420800	50	50 - 54	67.0	159.0	105	26.50212	NORMAL	
27	38	10	11043907200	66	65 - 69	67.0	144.0	79	32.31096	NORMAL	
28	39	10	10948089600	69	65 - 69	70.5	148.5	40	31.96953	OSTEOPOROSIS	
29	40	10	11051251200	66	65 - 69	66.5	147.0	48	30.77421	OSTEOPOROSIS	
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3. Bivariate analysis

Bivariate analysis

- Involves the analysis of **two** variables for the purpose of determining the empirical relationship between them.



easiest way is to measure how those two variables
simultaneously change together

3. Bivariate analysis

Bivariate analysis

- Involves the analysis of **two** variables for the purpose of determining the empirical relationship between them.



easiest way is to measure how those two variables
simultaneously change together

- Major differentiating point between *univariate* and *bivariate* analysis (a part from the number of variables implicated) is that bivariate analysis goes beyond simply **descriptive**, since it study the **relationship** between the two variables.

3. Bivariate analysis

Why bivariate analysis?

Let's begin by asking if:

People tend to marry other people of about the same age?

Our experience tells us “yes”, but how good is the correspondence?

Husband	36	72	37	36	51	50	47	50	37	41
Wife	35	67	33	35	50	46	47	42	36	41

Sample of spousal ages of 10 White American Couples

3. Bivariate analysis

Why bivariate analysis?



	Mean	Standard Deviation
Husbands	49	11
Wives	47	11

3. Bivariate analysis

Why bivariate analysis?

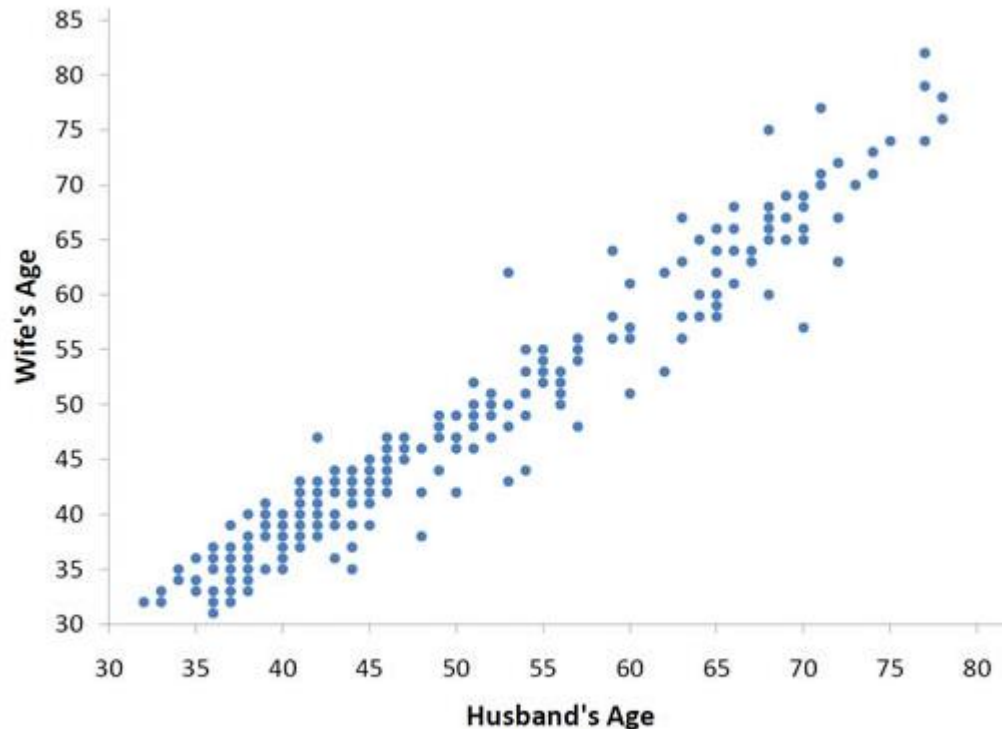


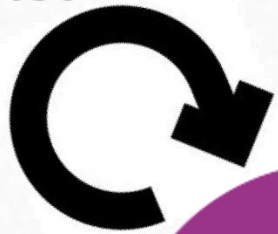
Figure 2. Scatter plot showing wife's age as a function of husband's age.

- ➡ The older the husband the older the wife.
- ➡ It is possible to know age of wives for an husband age.

3. Bivariate analysis

Some plots to study the relationship between two variables...

Barplot



Qualitative

Boxplot
Histogram



Quantitative

Scatterplot



3. Bivariate analysis

3.1 Qualitative versus qualitative

osteo											
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3. Bivariate analysis

3.1 Qualitative versus qualitative

The way to study the relation will depend on the variable types:

- Two **qualitative** variables: contingency table



Used for organizing categorical variables and testing hypothesis with the chi-squared test for independence

3. Bivariate analysis

3.1 Qualitative versus qualitative

The way to study the relation will depend on the variable types:

- Two **qualitative** variables: contingency table



Used for organizing categorical variables and testing hypothesis with the chi-squared test for independence

- Count of individuals that simultaneously presents variable 1 (x) and variable 2 (y)

	y_1	y_2	\cdots	y_p	$n_{i.}$
x_1	n_{11}	n_{12}	\cdots	n_{1p}	$n_{1.}$
x_2	n_{21}	n_{22}	\cdots	n_{2p}	$n_{2.}$
\vdots	\vdots	\vdots	\vdots	\vdots	\vdots
x_k	n_{k1}	n_{k2}	\cdots	n_{kp}	$n_{k.}$
$n_{.j}$	$n_{.1}$	$n_{.2}$	\cdots	$n_{.p}$	N

Absolute

$$f_{ij} = \frac{n_{ij}}{N}$$



	y_1	y_2	\cdots	y_p	$f_{i.}$
x_1	f_{11}	f_{12}	\cdots	f_{1p}	$f_{1.}$
x_2	f_{21}	f_{22}	\cdots	f_{2p}	$f_{2.}$
\vdots	\vdots	\vdots	\vdots	\vdots	\vdots
x_k	f_{k1}	f_{k2}	\cdots	f_{kp}	$f_{k.}$
$f_{.j}$	$f_{.1}$	$f_{.2}$	\cdots	$f_{.p}$	1

relative

3. Bivariate analysis

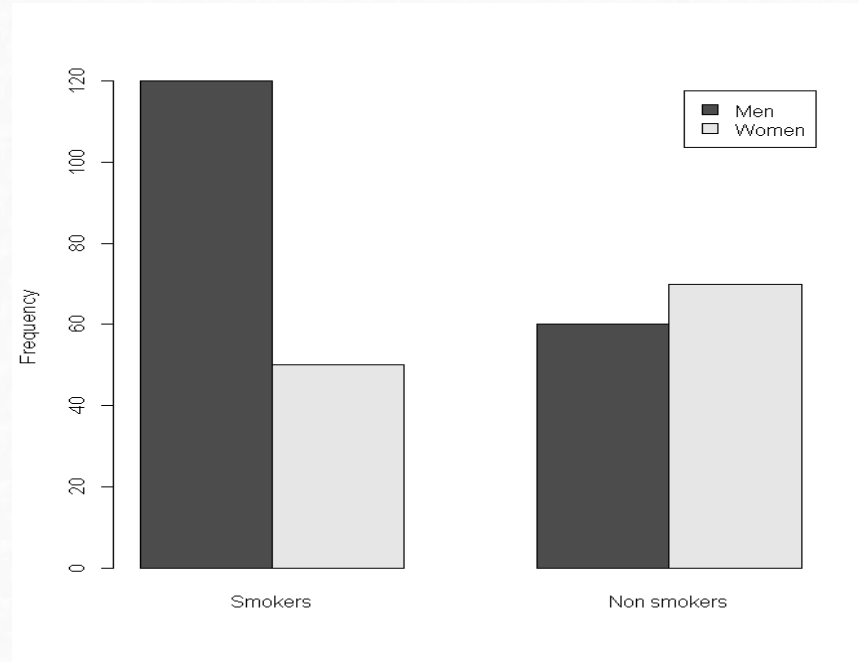
3.1 Qualitative versus qualitative

An study wants to know if there are differences about smoking habits in men and women.

Gender	Smoking habits
1	1
2	1
1	0
1	0
1	0
1	1
2	1
...	...



	Smokers	Non Smoking	Total
Men	120	60	180
Women	50	70	120
Total	170	130	300



3. Bivariate analysis

3.1 Qualitative versus qualitative

Let's do in R :

Study if the group age (*grupedad*) of patients, influence in the illness type (*clasific*):

```
osteoporosis <- rio::import("datasets/osteoporosis.csv",dec = ",")
```

```
require(gmodels)
```

```
gmodels::CrossTable(osteoporosis$grupedad, osteoporosis$clasific, prop.c  
= F, prop.r = F,prop.chisq = F)
```

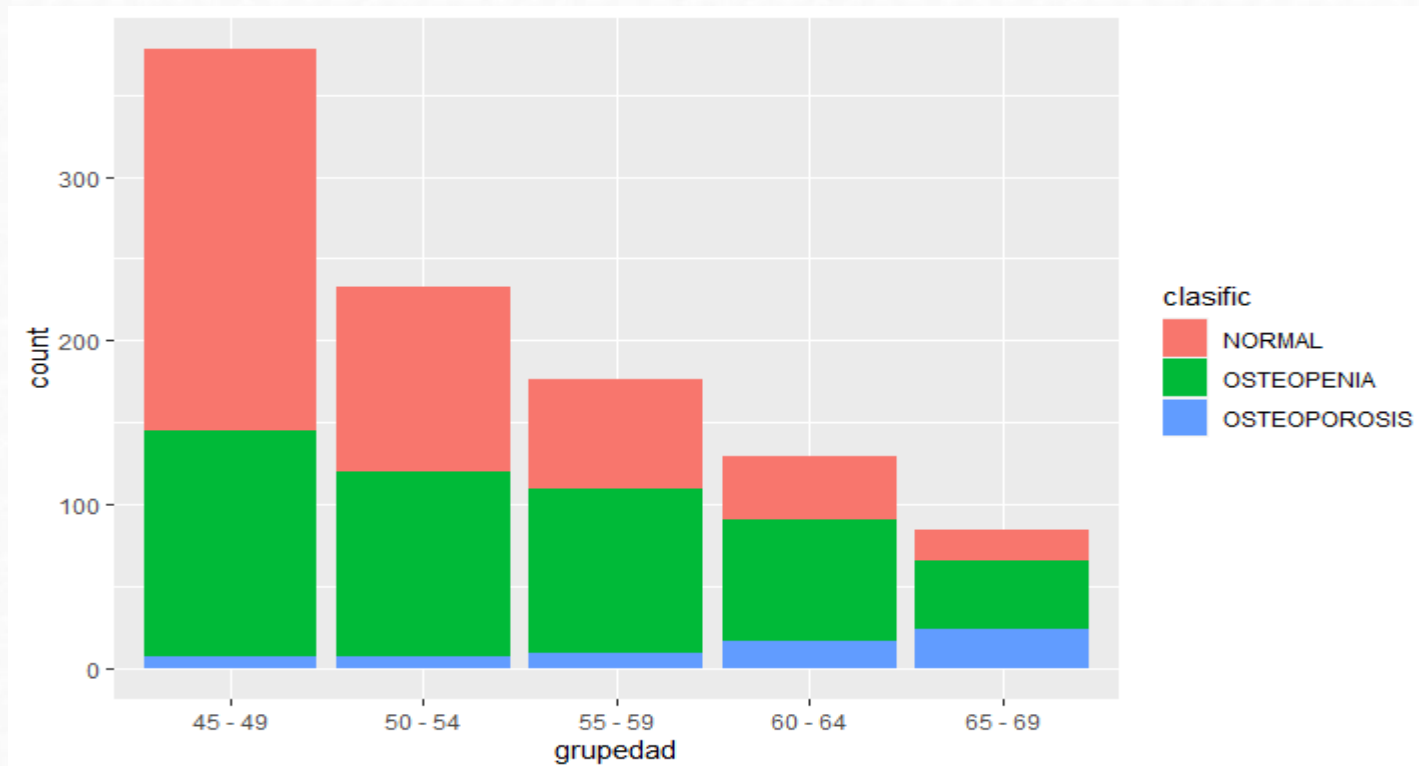
Cell Contents				
				N
				N / Table Total
Total Observations in Table: 1000				
osteoporosis\$grupedad	osteoporosis\$clasific			Row Total
	NORMAL	OSTEOPENIA	OSTEOPOROSIS	
45 - 49	233 0.233	138 0.138	7 0.007	378
50 - 54	113 0.113	113 0.113	7 0.007	233
55 - 59	67 0.067	100 0.100	9 0.009	176
60 - 64	38 0.038	74 0.074	17 0.017	129
65 - 69	18 0.018	42 0.042	24 0.024	84
Column Total	469	467	64	1000

3. Bivariate analysis

3.1 Qualitative versus qualitative

Barplot with R

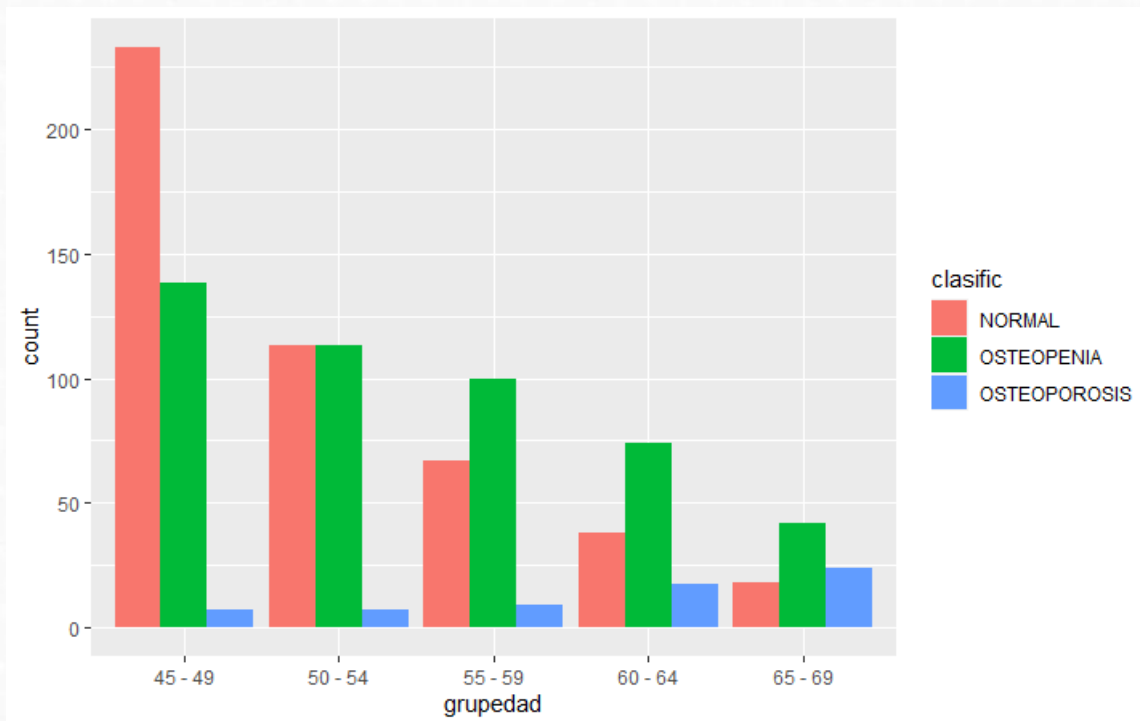
```
ggplot(data = osteoporosis, aes(x = grupedad)) +  
  geom_bar(aes(fill = clasific))
```



3. Bivariate analysis

3.1 Qualitative versus qualitative

```
ggplot(data = osteoporosis, aes(x = grupedad)) +  
  geom_bar(aes(fill = clasific), position = "dodge")
```



3. Bivariate analysis

3.1 Qualitative versus qualitative

Improving barplot

<http://www.sthda.com/english/wiki/ggplot2-barplots-quick-start-guide-r-software-and-data-visualization>

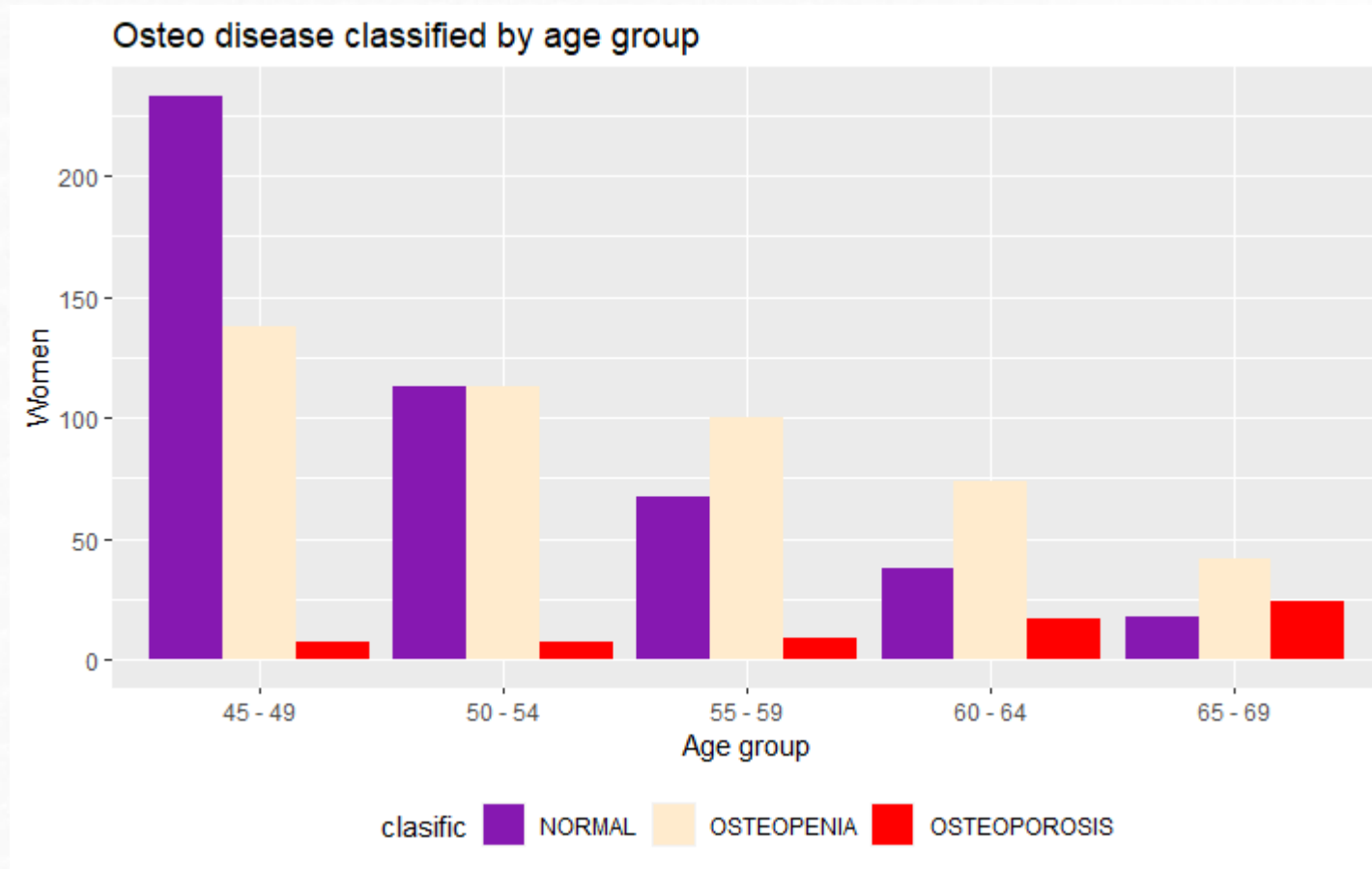
Change colors, legend position, labels and finally save it!

```
p + scale_fill_manual(values=c("#8618b1", "blanchedalmond", "red"))  
  
p + theme(legend.position="bottom")  
  
p + labs(x = "Age group", y = "Women", title = "Osteo disease classified by age group")  
  
pdf("clasific_grupedad.pdf")  
  p + labs(x = "Age group", y = "Women", title = "Osteo disease classified by age group")  
dev.off()
```


3. Bivariate analysis

3.1 Qualitative versus qualitative

Improving barplot



3. Bivariate analysis

3.2 Qualitative versus quantitative

osteo											
	registro	area	f_nac	edad	grupedad	peso	talla	bua	imc	clasific	me
1	3	10	11659420800	57	55 - 59	70.0	168.0	69	24.80159	OSTEOPENIA	
2	4	10	11671689600	46	45 - 49	53.0	152.0	73	22.93975	OSTEOPENIA	
3	10	10	11721024000	45	45 - 49	64.0	158.0	81	25.63692	NORMAL	
4	11	10	11464416000	53	50 - 54	78.0	161.0	58	30.09143	OSTEOPENIA	
5	12	10	11690784000	46	45 - 49	56.0	157.0	89	22.71897	NORMAL	
6	15	10	11716012800	45	45 - 49	63.5	170.0	76	21.97232	NORMAL	
7	16	10	11623737600	48	45 - 49	86.0	161.0	87	33.17773	NORMAL	
8	17	10	11562307200	50	50 - 54	61.5	164.0	74	22.86585	NORMAL	
9	18	10	11538028800	51	50 - 54	60.5	158.0	58	24.23490	OSTEOPENIA	
10	20	10	11332483200	57	55 - 59	64.0	149.0	61	28.82753	OSTEOPENIA	
11	21	10	11631945600	48	45 - 49	70.3	160.0	67	27.46094	OSTEOPENIA	
12	22	10	11425536000	55	55 - 59	74.4	160.0	68	29.06250	OSTEOPENIA	
13	23	10	11553235200	50	50 - 54	55.5	154.5	73	23.25070	OSTEOPENIA	
14	24	10	11367302400	56	55 - 59	89.0	166.0	61	32.29787	OSTEOPENIA	
15	25	10	11585635200	49	45 - 49	50.6	157.0	68	20.52822	OSTEOPENIA	
16	26	10	11572156800	50	50 - 54	71.4	152.0	74	30.90374	NORMAL	
17	27	10	11590992000	49	45 - 49	78.0	157.0	62	31.64429	OSTEOPENIA	
18	28	10	11293516800	58	55 - 59	72.0	162.0	65	27.43484	OSTEOPENIA	
19	29	10	11215238400	61	60 - 64	68.0	155.5	65	28.12212	OSTEOPENIA	
20	30	10	11405664000	55	55 - 59	75.0	161.0	92	28.93407	NORMAL	
21	31	10	11633155200	48	45 - 49	66.5	153.0	11	28.40788	OSTEOPOROSIS	
22	32	10	11287728000	59	55 - 59	101.0	156.0	82	41.50230	NORMAL	
23	34	10	10992758400	68	65 - 69	66.5	145.0	57	31.62901	OSTEOPENIA	
24	35	10	10909382400	69	65 - 69	70.0	168.0	48	24.80159	OSTEOPOROSIS	
25	36	10	11643868800	48	45 - 49	60.1	153.0	86	25.67389	NORMAL	
26	37	10	11551420800	50	50 - 54	67.0	159.0	105	26.50212	NORMAL	
27	38	10	11043907200	66	65 - 69	67.0	144.0	79	32.31096	NORMAL	
28	39	10	10948089600	69	65 - 69	70.5	148.5	40	31.96953	OSTEOPOROSIS	
29	40	10	11051251200	66	65 - 69	66.5	147.0	48	30.77421	OSTEOPOROSIS	
30	41	10	11333692800	57	55 - 59	58.5	142.0	80	29.01210	NORMAL	

3. Bivariate analysis

3.2 Qualitative versus quantitative

The way to study the relation will depend on the variable types:

- One **qualitative** variable and one **quantitative** variable: Table of statistics



Mean value of the variable in each category for each individual

3. Bivariate analysis

3.2 Qualitative versus quantitative

Let's do it in R:

Osteoporosis dataset

Study if bone density (*bua*) changes depending the age group

```
library(dplyr)
osteoporosis %>%
  group_by(grupedad) %>%
  summarize(mean(edad))
```

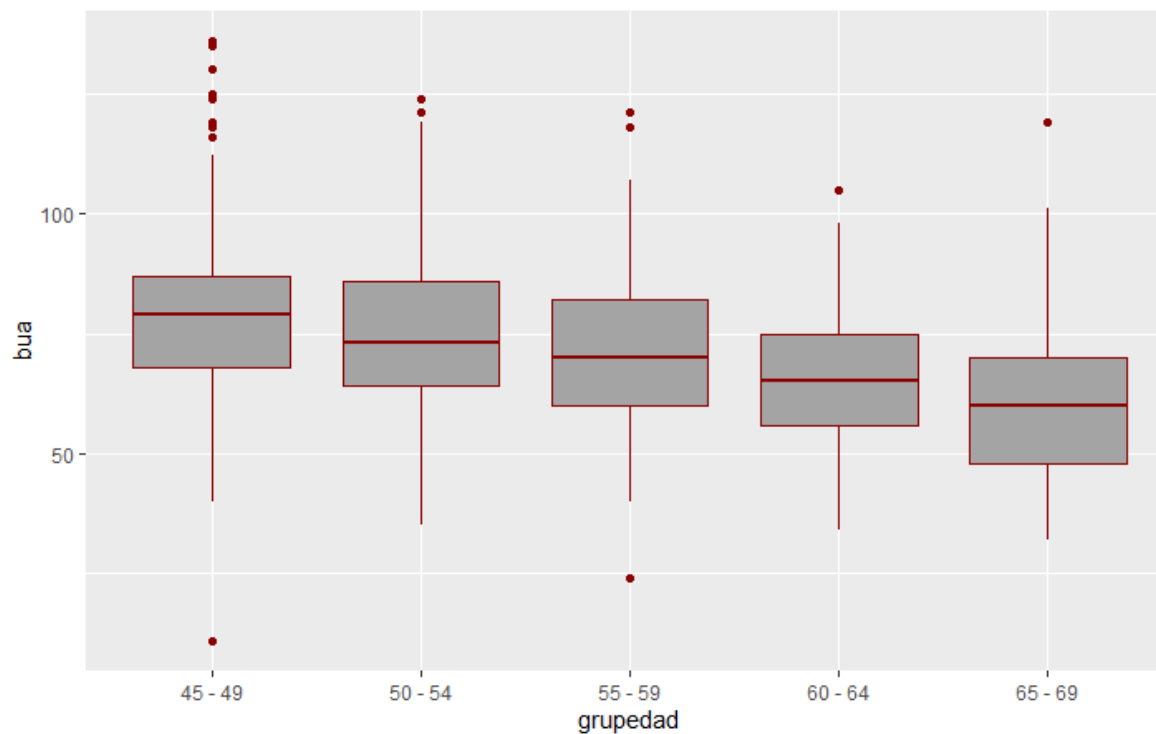
45-49	50-54	55-59	60-64	65-69
78.75926	75.05150	71.43182	64.89147	60.66667

3. Bivariate analysis

3.2 Qualitative versus quantitative

Study if bone density (*bua*) is related with the age group

```
bp <- ggplot(osteoporosis, aes(x = grupedad, y = bua)) +  
  geom_boxplot(fill='#A4A4A4', color="darkred")  
bp
```



3. Bivariate analysis

3.2 Qualitative versus quantitative

Study if bone density (*bua*) is related with the age group

```
# Box plot with points  
# 0.2 : degree of jitter in x direction  
bp + geom_jitter(shape = 16, position = position_jitter(0.2)) +  
  labs(x = "Age Group", y = "Women", title = "Osteo disease classified by age group")
```



3. Bivariate analysis

Exercise

Study the relationship between *menop* and group of illness (*classific*)

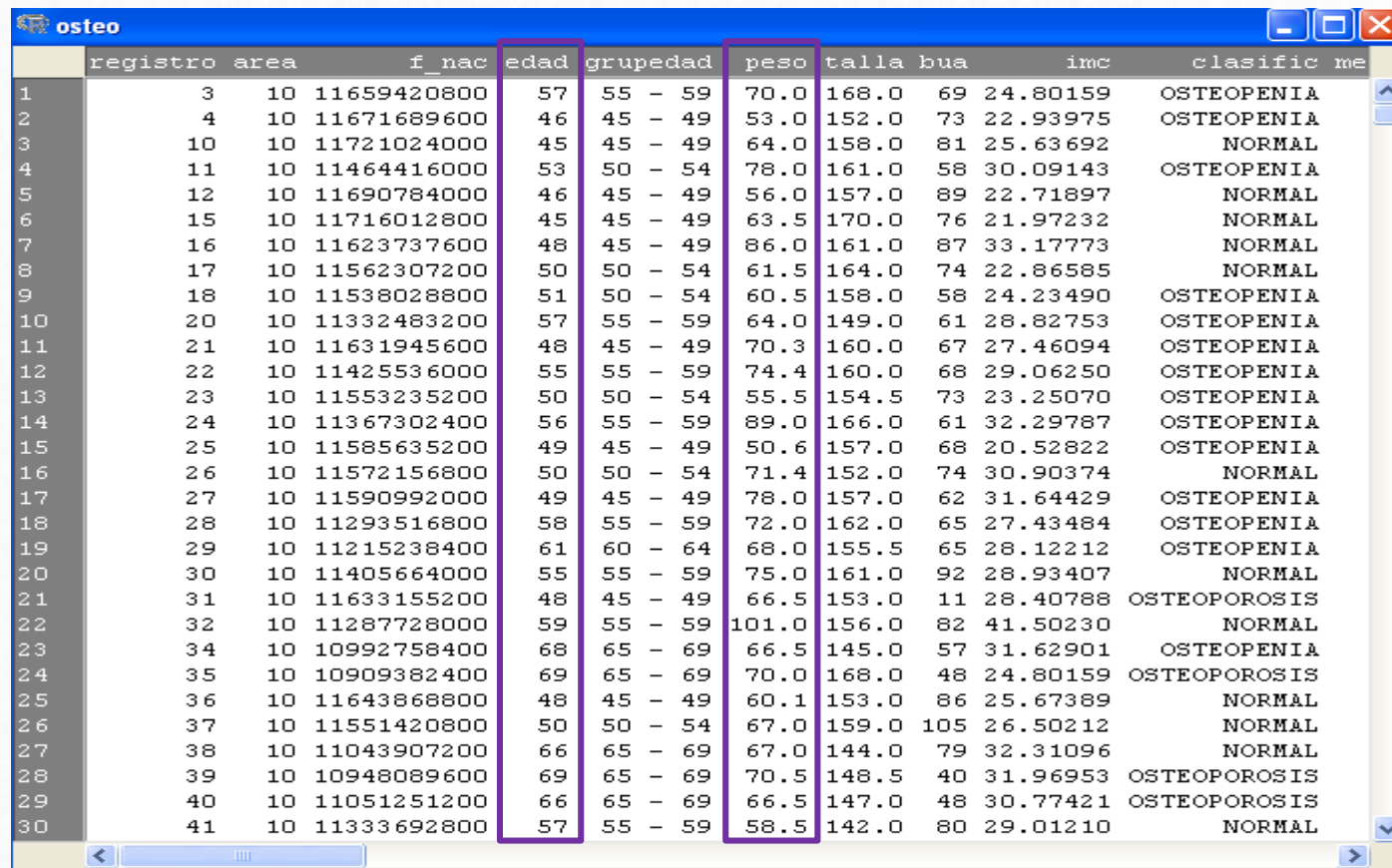
Study the relationship between *peso i* and group of illness (*classific*).

3. Bivariate analysis

3.3 Quantitative versus Quantitative

The way to study the relation will depend on the variable types:

- Two **quantitatives** variables:



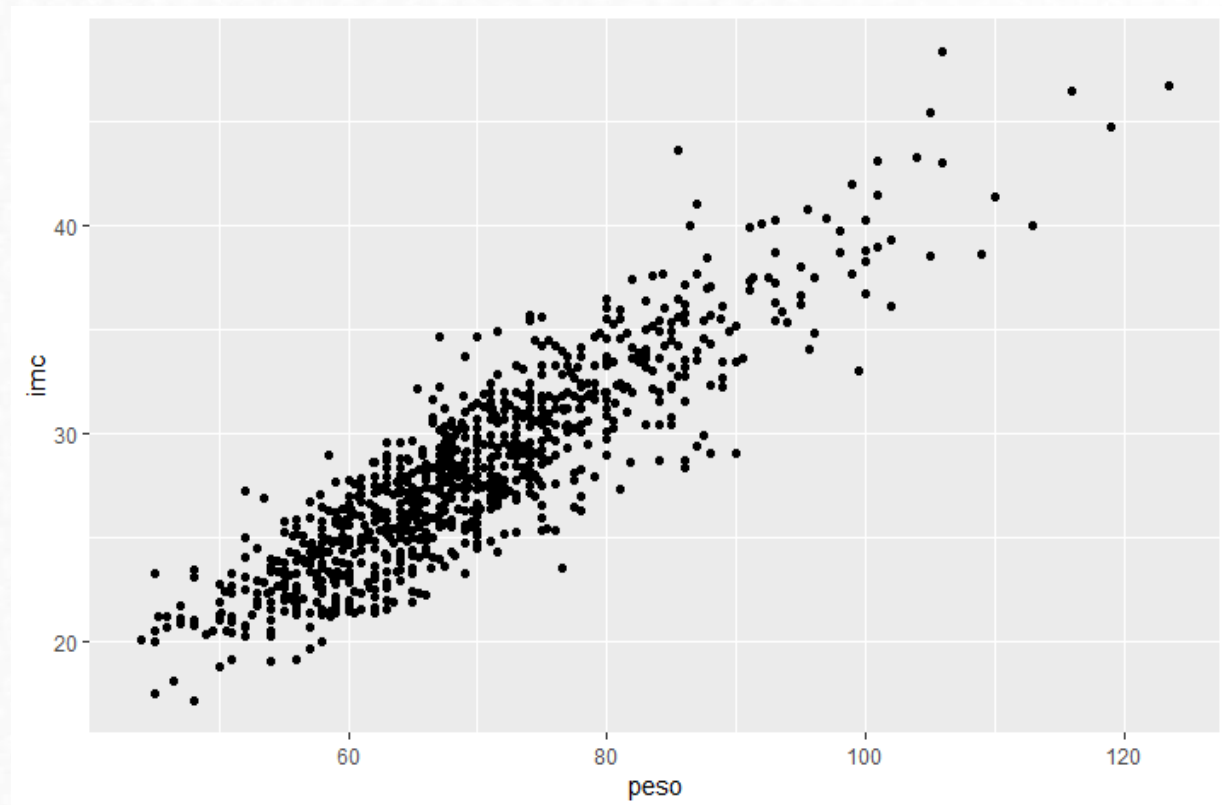
	registro	area	f_nac	edad	grupedad	peso	talla	bua	imc	clasific me
1	3	10	11659420800	57	55 - 59	70.0	168.0	69	24.80159	OSTEOPENIA
2	4	10	11671689600	46	45 - 49	53.0	152.0	73	22.93975	OSTEOPENIA
3	10	10	11721024000	45	45 - 49	64.0	158.0	81	25.63692	NORMAL
4	11	10	11464416000	53	50 - 54	78.0	161.0	58	30.09143	OSTEOPENIA
5	12	10	11690784000	46	45 - 49	56.0	157.0	89	22.71897	NORMAL
6	15	10	11716012800	45	45 - 49	63.5	170.0	76	21.97232	NORMAL
7	16	10	11623737600	48	45 - 49	86.0	161.0	87	33.17773	NORMAL
8	17	10	11562307200	50	50 - 54	61.5	164.0	74	22.86585	NORMAL
9	18	10	11538028800	51	50 - 54	60.5	158.0	58	24.23490	OSTEOPENIA
10	20	10	11332483200	57	55 - 59	64.0	149.0	61	28.82753	OSTEOPENIA
11	21	10	11631945600	48	45 - 49	70.3	160.0	67	27.46094	OSTEOPENIA
12	22	10	11425536000	55	55 - 59	74.4	160.0	68	29.06250	OSTEOPENIA
13	23	10	11553235200	50	50 - 54	55.5	154.5	73	23.25070	OSTEOPENIA
14	24	10	11367302400	56	55 - 59	89.0	166.0	61	32.29787	OSTEOPENIA
15	25	10	11585635200	49	45 - 49	50.6	157.0	68	20.52822	OSTEOPENIA
16	26	10	11572156800	50	50 - 54	71.4	152.0	74	30.90374	NORMAL
17	27	10	11590992000	49	45 - 49	78.0	157.0	62	31.64429	OSTEOPENIA
18	28	10	11293516800	58	55 - 59	72.0	162.0	65	27.43484	OSTEOPENIA
19	29	10	11215238400	61	60 - 64	68.0	155.5	65	28.12212	OSTEOPENIA
20	30	10	11405664000	55	55 - 59	75.0	161.0	92	28.93407	NORMAL
21	31	10	11633155200	48	45 - 49	66.5	153.0	11	28.40788	OSTEOPOROSIS
22	32	10	11287728000	59	55 - 59	101.0	156.0	82	41.50230	NORMAL
23	34	10	10992758400	68	65 - 69	66.5	145.0	57	31.62901	OSTEOPENIA
24	35	10	10909382400	69	65 - 69	70.0	168.0	48	24.80159	OSTEOPOROSIS
25	36	10	11643868800	48	45 - 49	60.1	153.0	86	25.67389	NORMAL
26	37	10	11551420800	50	50 - 54	67.0	159.0	105	26.50212	NORMAL
27	38	10	11043907200	66	65 - 69	67.0	144.0	79	32.31096	NORMAL
28	39	10	10948089600	69	65 - 69	70.5	148.5	40	31.96953	OSTEOPOROSIS
29	40	10	11051251200	66	65 - 69	66.5	147.0	48	30.77421	OSTEOPOROSIS
30	41	10	11333692800	57	55 - 59	58.5	142.0	80	29.01210	NORMAL

3. Bivariate analysis

3.3 Quantitative versus Quantitative

Basic scatter plot

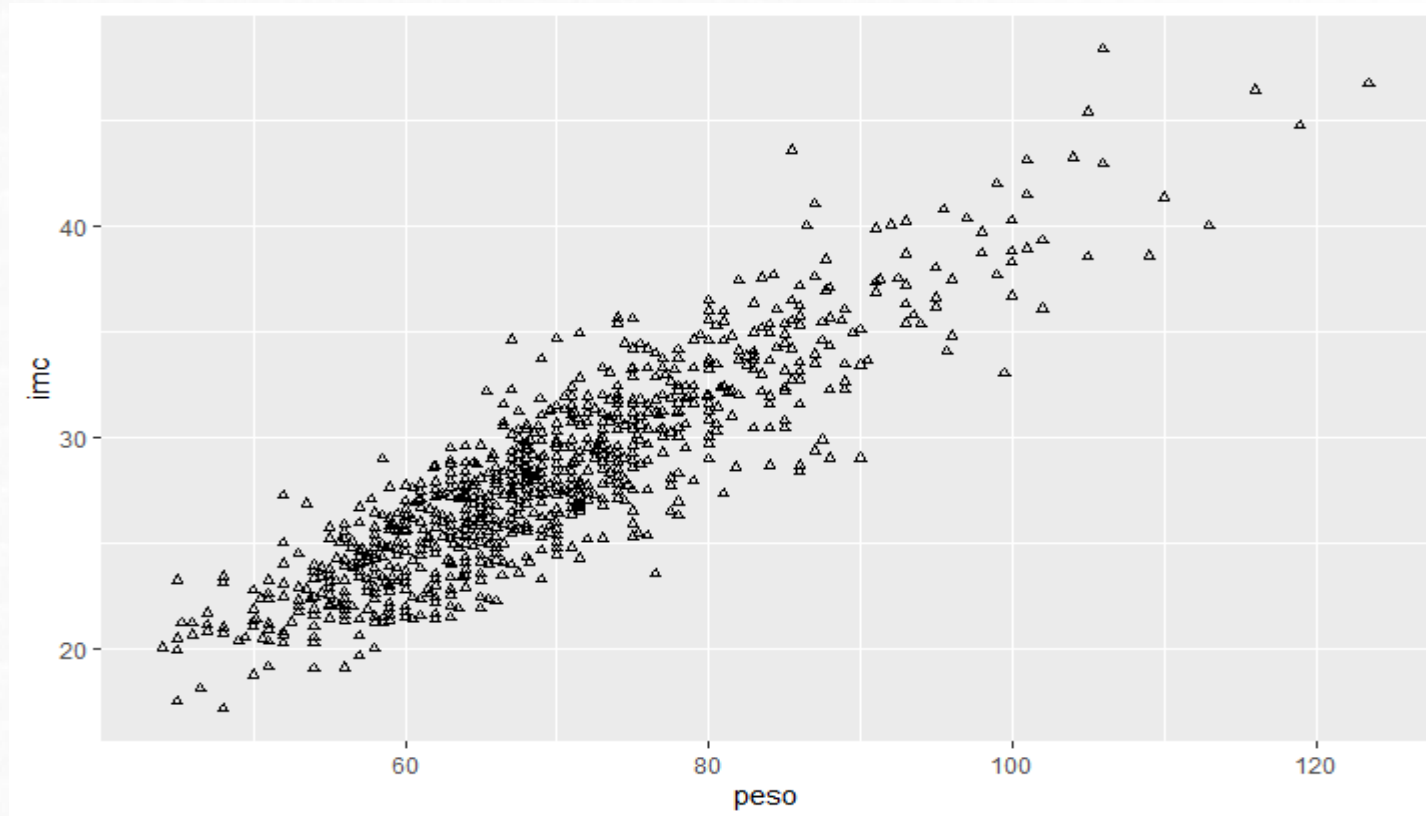
```
ggplot(osteoporosis, aes(x = peso, y = imc)) +  
  geom_point()
```



3. Bivariate analysis

3.3 Quantitative versus Quantitative

```
# Change the point size, and shape  
ggplot(osteoporosis, aes(x = peso, y = imc)) +  
  geom_point(size = 1, shape = 1)
```

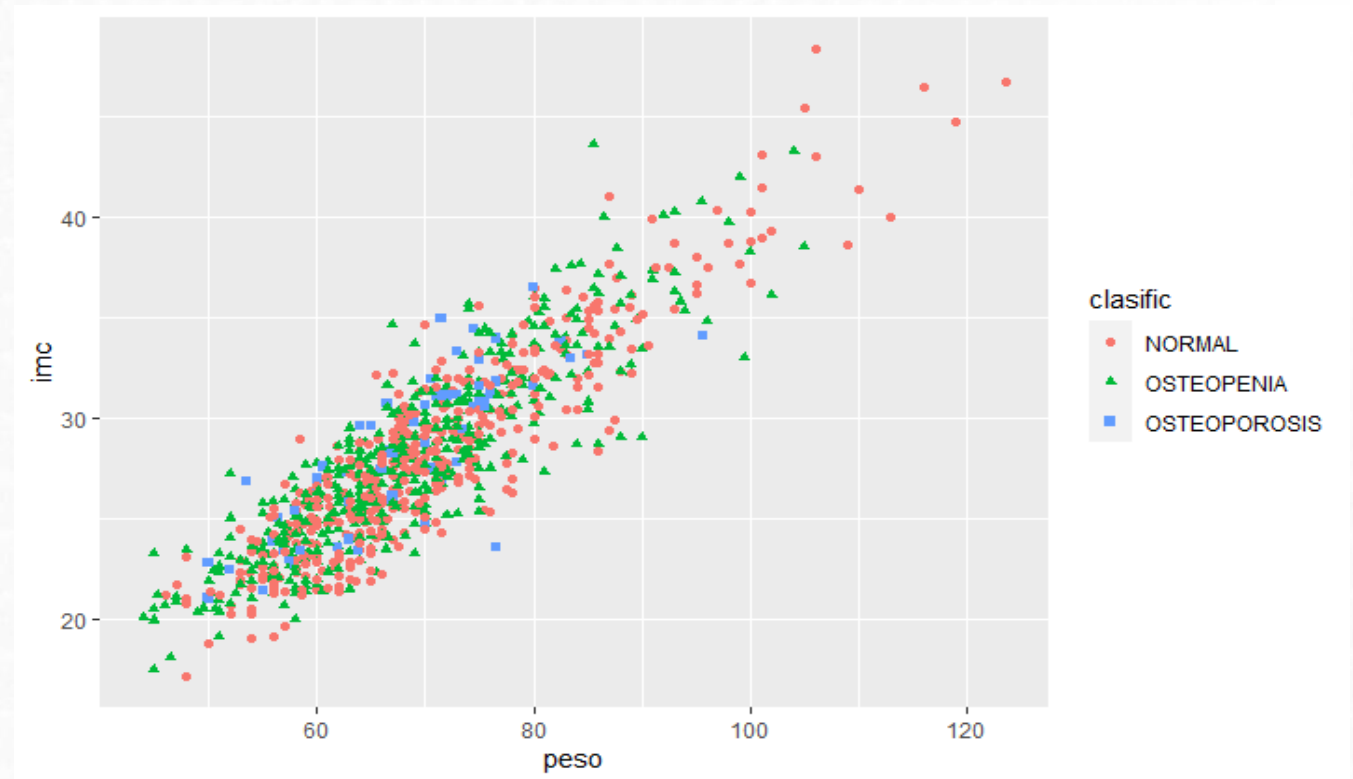


3. Bivariate analysis

3.3 Quantitative versus Quantitative

Color the points depending of another variable

```
ggplot(osteoporosis, aes(x = peso, y = imc, color = clasific, shape = clasific)) +  
  geom_point()
```



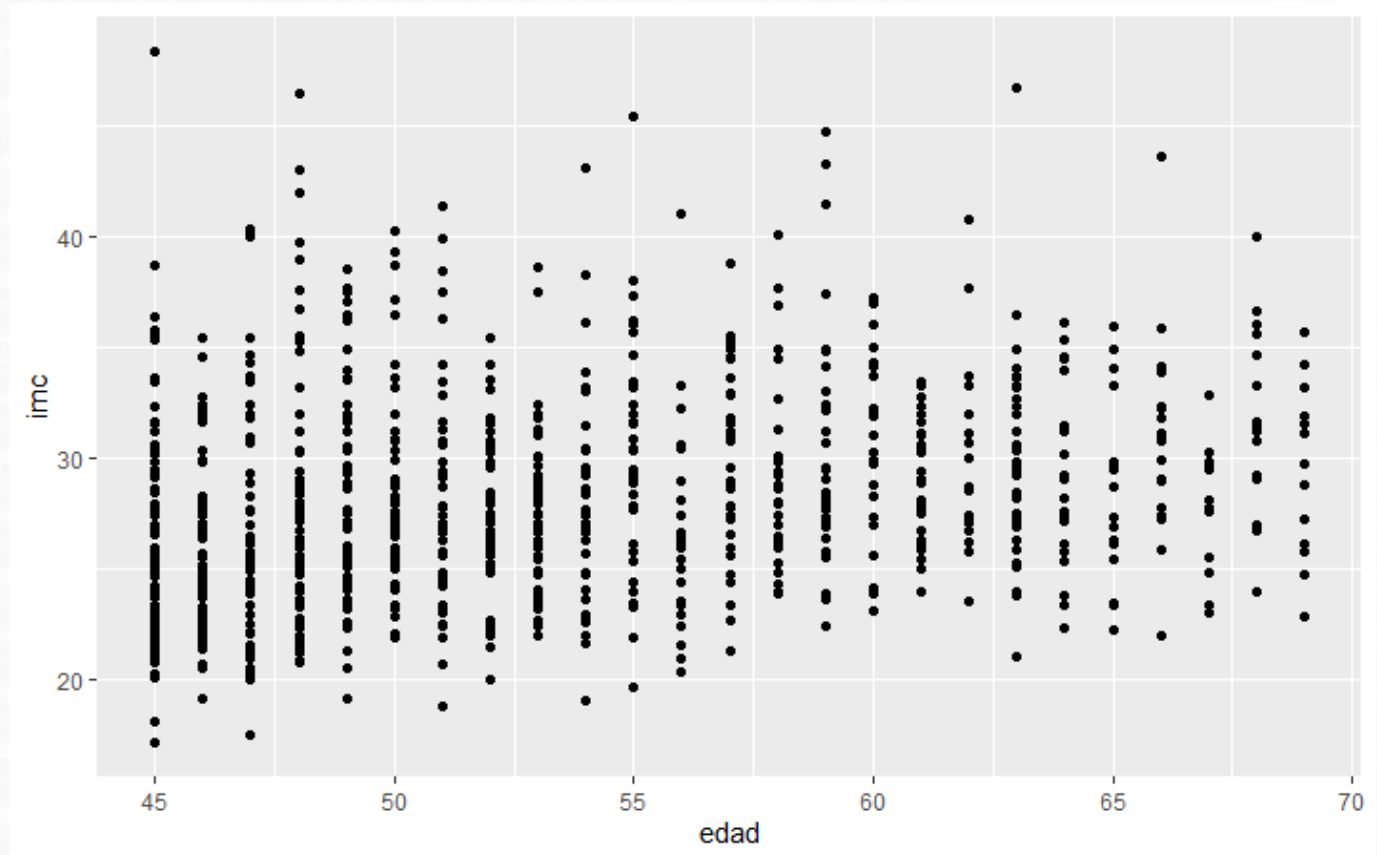
3. Bivariate analysis

3.3 Quantitative versus Quantitative

But not always the correlation is good!

```
ggplot(osteoporosis, aes(x = edad, y = imc)) +  
  geom_point()
```

Whatever you compute
Always look at the
data!



3. Bivariate analysis

3.3 Quantitative versus Quantitative

```
library(GGally)
```

```
ggpairs(osteoporosis, columns = c("edad", "peso", "talla", "imc", "bua", "menarqui"),  
ggplot2::aes(colour = clasific))
```

3. Bivariate analysis

3.3 Quantitative versus Quantitative

```
library(GGally)
```

```
ggpairs(osteoporosis, columns = c("edad", "peso", "talla", "imc", "bua", "menarqui"),  
ggplot2::aes(colour = clasific))
```

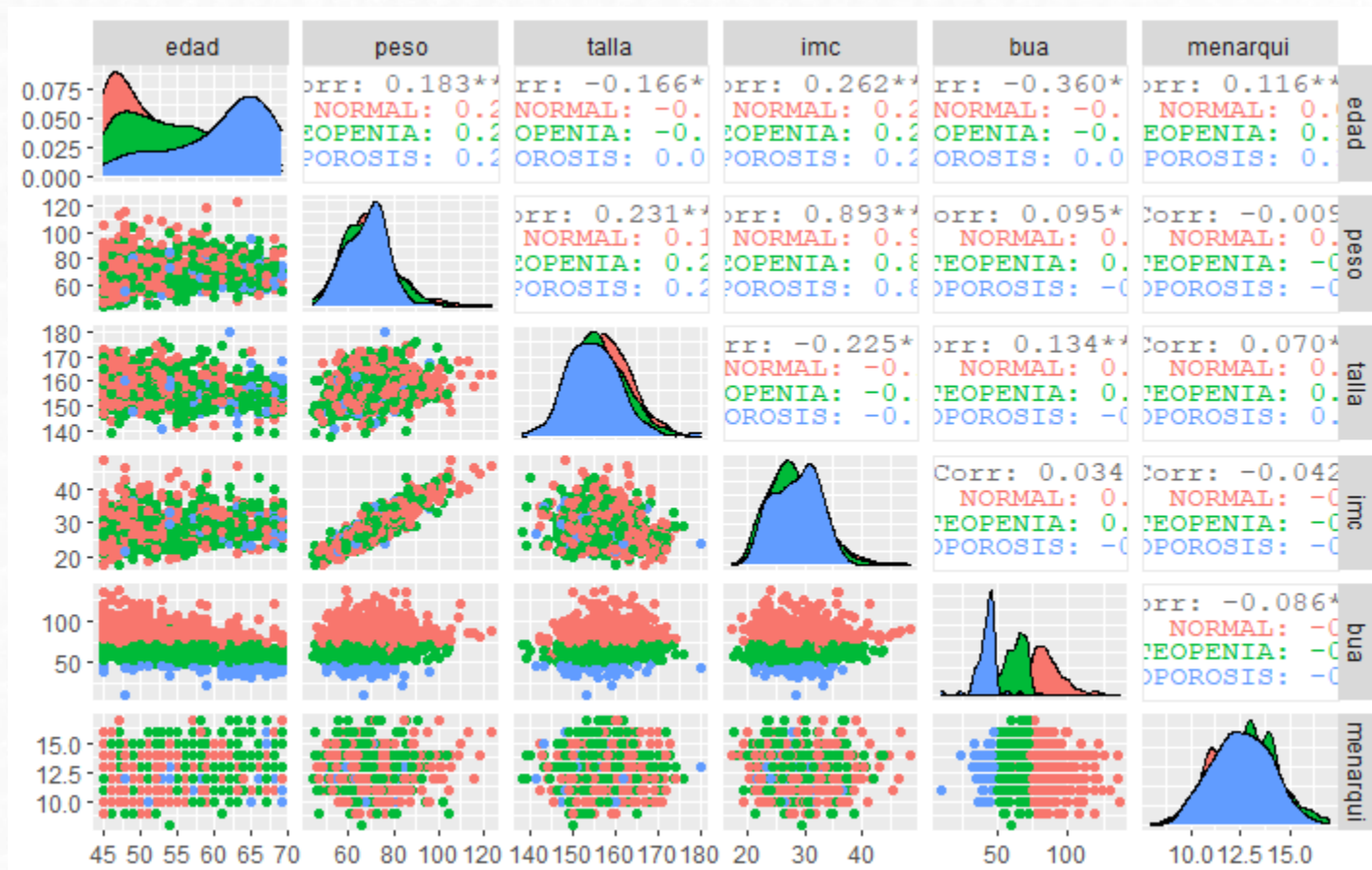


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4. Correlation

1. Definition
2. Types of correlation (Pearson, Spearman)

4. Correlation

1. Definition

Main characteristics of correlation analysis:

- Correlation analysis allows
 - To study the **way** of relation between the two variables
 - To **quantify** the intensity of relation
- Correlation is **not causation** ➡ one thing does not causes the other
- In the correlation analysis, the two variables have the **same weight**
- The **correlation coefficient** measures the strength of a **linear** relation

4. Correlation

2. Types of correlation

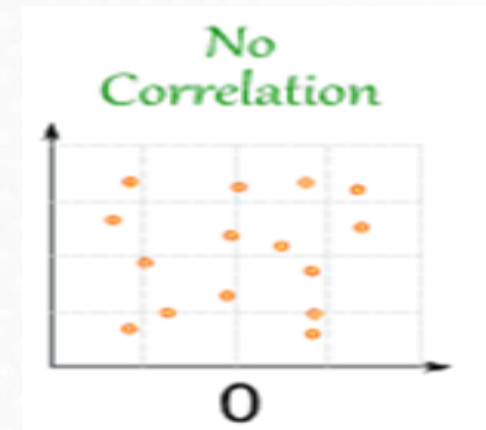
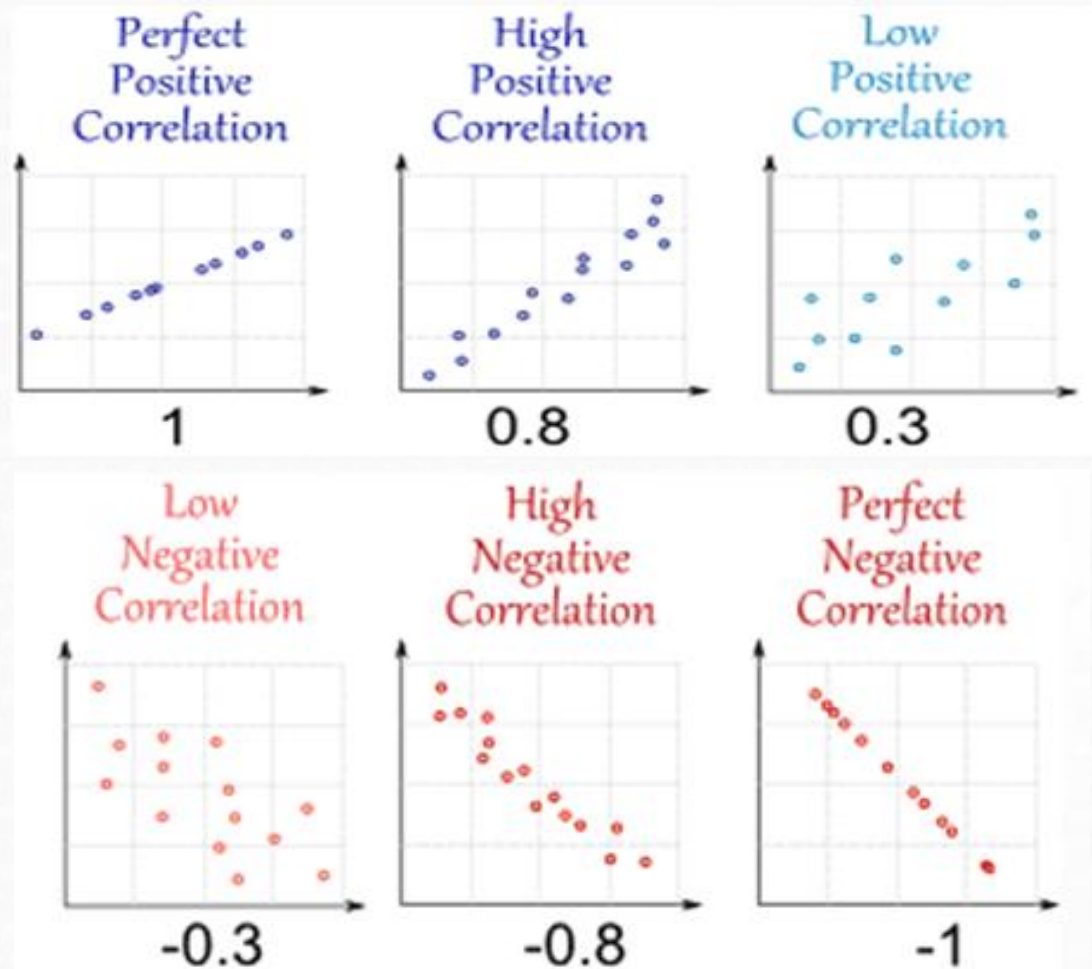
Pearson correlation coefficient

- Measures linear correlation between two variables
- It is represented by letter **r**. It has no dimensions (no units)
- Values go from **-1** to **+1**
 - **r=0** indicates no linear relation between the variables
 - **r>0** indicates direct relation between the variables
 - **r<0** indicates indirect relation between the variables
 - **r=1/-1** indicates a perfect relation between the variables

4. Correlation

2. Types of correlation

Pearson correlation coefficient. Examples

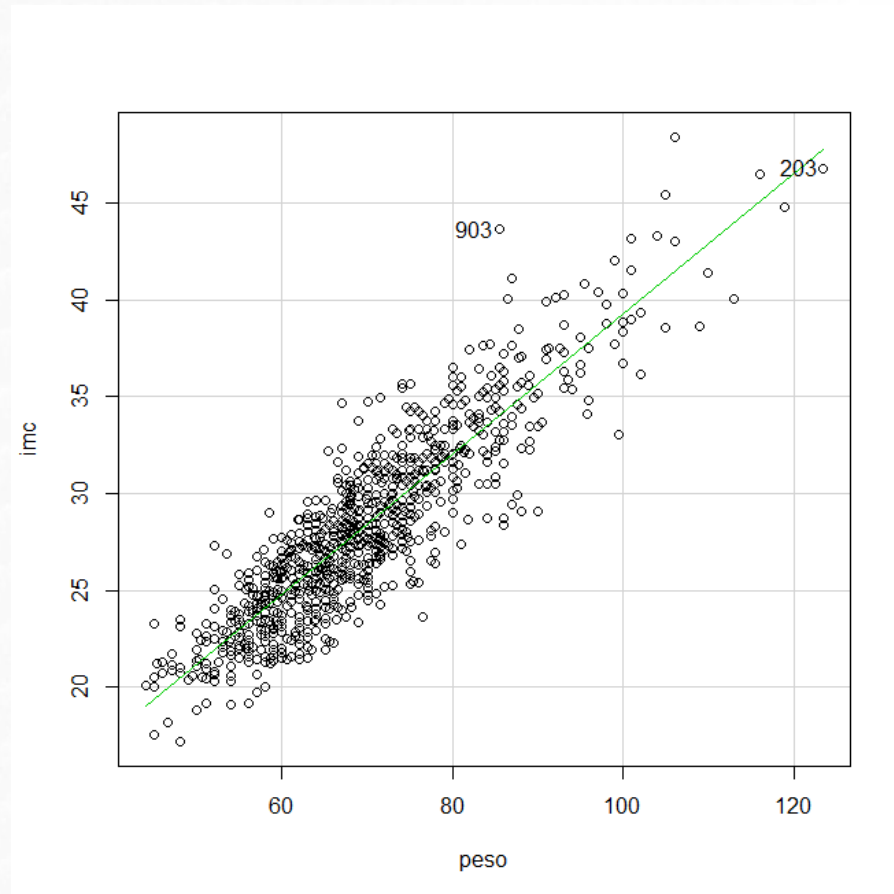


4. Correlation

2. Types of correlation

Study the relationship between *peso* and *body mass index (imc)*:

```
      imc      peso
imc  1.000000  0.8927967
peso 0.8927967  1.0000000
```



4. Correlation

2. Types of correlation

Pearson correlation coefficient. How to in R?

Bone density and **age** are correlated?

```
cor(osteoporosis$bua, osteoporosis$edad, method = "pearson")
```

```
[1] -0.3601883
```

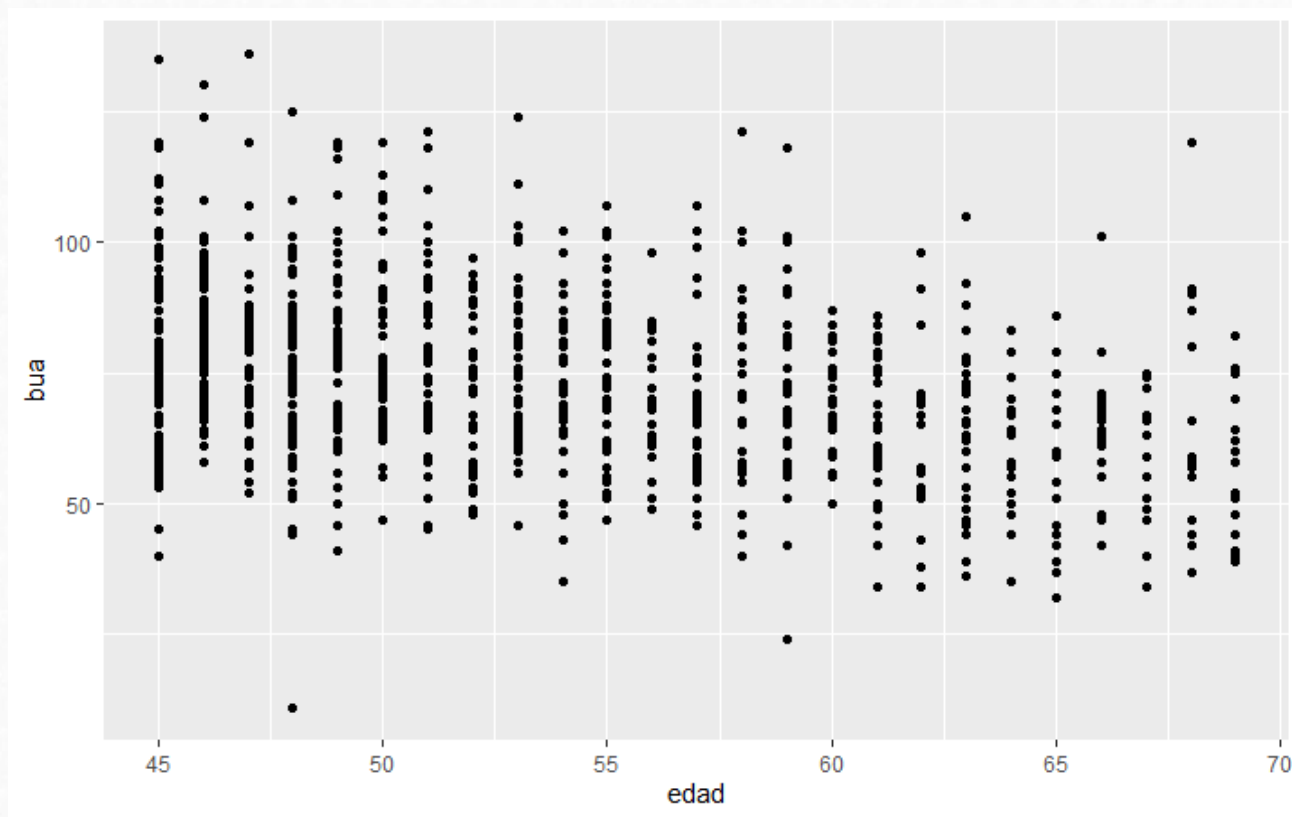
Don't forget to look the graphic!!

4. Correlation

2. Types of correlation

Pearson correlation coefficient. How to in R-commander?

```
ggplot(osteoporosis, aes(x = edad, y = bua)) +  
  geom_point()
```



4. Correlation

2. Types of correlation

Pearson correlation coefficient. How to in R?

Exercise 1. Do you think that exists a relationship between *peso* and *talla*? What type of relationship? Show a scatterplot of the values.

4. Correlation

2. Types of correlation

Non Parametric correlation: Spearman correlation coefficient

- Pearson correlation coefficient is severely affected by **outliers** and if the relation is not linear



Better to use **Spearman** correlation coefficient (use the ranks between the numbers instead the values) to calculate the correlation coefficient

- Evaluates the **monotonic** relationship between the variables (not the **linear** relationship as Pearson does).

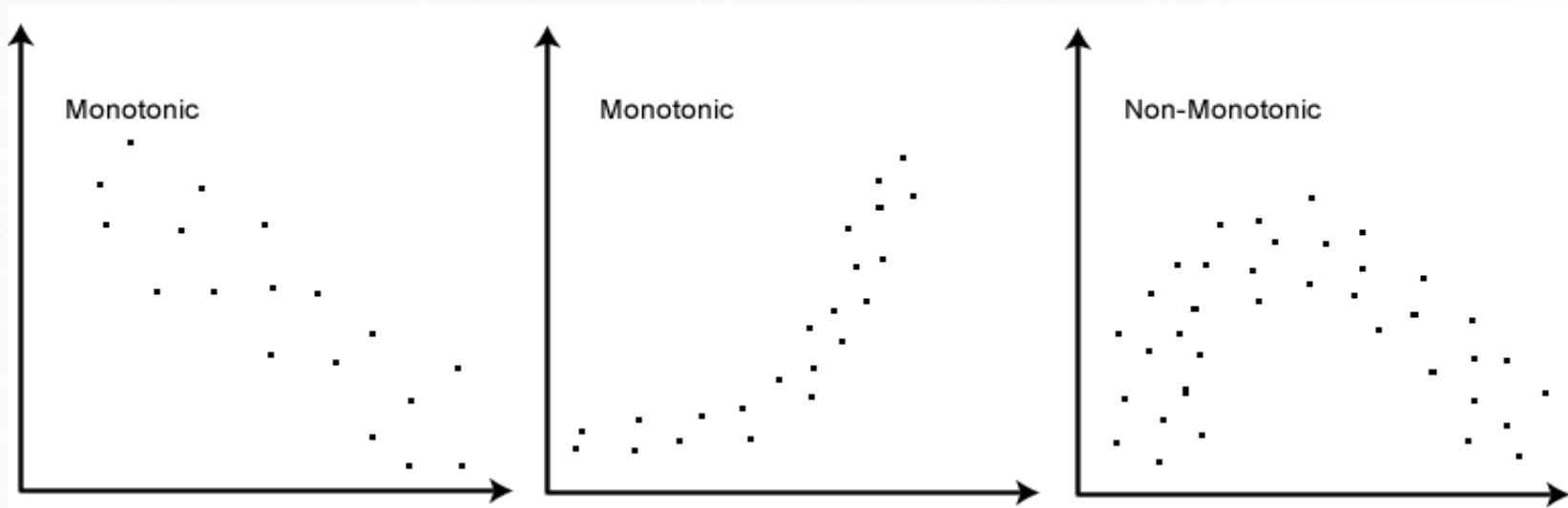


The variables tend to change together but not necessarily at a constant rate

4. Correlation

2. Types of correlation

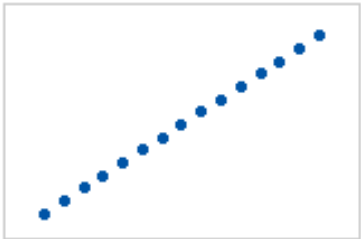
Non Parametric correlation: Spearman correlation coefficient



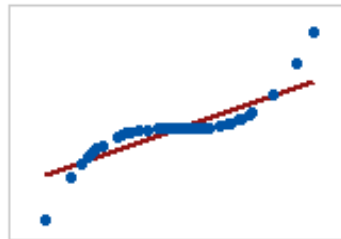
4. Correlation

2. Types of correlation

Comparison of Pearson and Spearman coefficients.



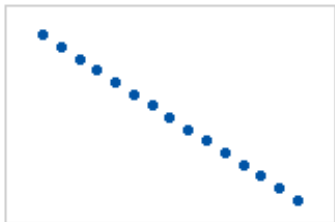
Pearson = +1, Spearman = +1



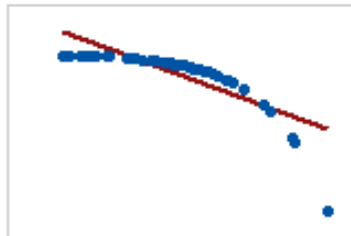
Pearson = +0.851, Spearman = +1



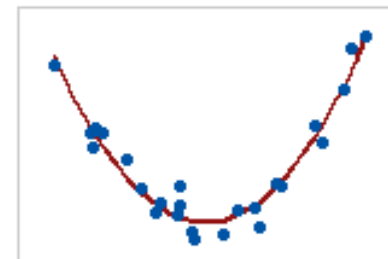
Pearson = -0.093, Spearman = -0.093



Pearson = -1, Spearman = -1



Pearson = -0.799, Spearman = -1



Coefficient of 0

Always examine a scatterplot to determine the form of the relationship

4. Correlation

2. Types of correlation

Spearman correlation coefficient. How to in R?

```
cor(osteoporosis$bua, osteoporosis$edad, method = "spearman")
```

```
[1] -0.3540295
```

4. Correlation

2. Types of correlation

Correlation matrix

```
cor(osteoporosis[, c("edad", "peso", "talla", "imc", "bua", "menarqui")])
```

	edad	peso	talla	imc	bua	menarqui
edad	1.0000000	0.182629245	-0.16635268	0.26173285	-0.36018834	0.115901253
peso	0.1826292	1.000000000	0.23110585	0.89278635	0.09467837	-0.008526465
talla	-0.1663527	0.231105848	1.00000000	-0.22546438	0.13350207	0.070002843
imc	0.2617329	0.892786346	-0.22546438	1.00000000	0.03415938	-0.041607661
bua	-0.3601883	0.094678365	0.13350207	0.03415938	1.00000000	-0.085935539
menarqui	0.1159013	-0.008526465	0.07000284	-0.04160766	-0.08593554	1.00000000

4. Correlation. Exercises

Exercise 2. An hypothetical study, published last year that exists a relation between ***age*** and ***systolic blood pressure (sbp)***? Do you think is it true? Show a scatterplot of the values? If not, find another variable in the dataset that has a good correlation with ***systolic blood pressure***.

Use dataset Framingham250.csv