

Statistics with R: Exploratory Data Analysis II and Plots with R

Basic Statistics with R
UEB-VHIR

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1. Definition
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1. Elegant graphics for data analysis

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

Hadley Wickham book

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

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

<https://www.rstudio.com/wp-content/uploads/2015/03/ggplot2-cheatsheet.pdf>

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 is a mapping of the **data** to the **aesthetic** attributes (position, colour, shape, size) of **geometric** objects (points, lines, bars, ...).
- Plot may also include statistical transformations (**stats**) of the data and information about plot's coordinate system (**coord**).
- Plot can be saved as an object in R
- Complex plots can be built layer by layer, where each **layer** can come from a different dataset and have a different aesthetic mappings, making it possible to display data from multiple sources.

1. Elegant graphics for data analysis

Basic components of a ggplot include:

- required**
 - A **data** frame: stores all of the data that can be plotted
 - **aesthetic** mappings: describe how data are mapped to color, size, shape, location (eg. indicates x, y variables)
 - **geoms** (geometric objects): defines the type of graphics (histogram, box plot, line plot, density plot, dot plot,)
- not required**
(defaults provided)
 - **facets**: split a plot in several panels
 - **stats**: statistical transformations like binning, quantiles, smoothing.
 - **scales**: what scale an aesthetic map uses (example: male = red, female = blue).
 - **coordinate** system: describes the system in which the locations of the geoms will be drawn
 - **theme**: font size, background colors, ...

1. Elegant graphics for data analysis

```
Plot = ggplot(data, aes(x = var1, y = var2, ...)) +  
  geom_X()
```

A WORLD OF GEOM

`ggplot2` builds charts through layers using `geom_` functions. Here is a list of the different available geoms. Click one to see an example using it.

[geom_bar](#)[geom_bin](#)[geom_boxplot](#)[geom_density](#)[geom_error](#)[geom_hex](#)[geom_hist](#)[geom_hline](#)[geom_jitter](#)[geom_label](#)[geom_line](#)[geom_point](#)[geom_polygon](#)[geom_rect](#)[geom_ribbon](#)[geom_rug](#)[geom_segment](#)[geom_smooth](#)[geom_text](#)[geom_tile](#)[geom_violin](#)[geom_vline](#)

<https://www.r-graph-gallery.com/ggplot2-package.html#LogoMenu>

1. Elegant graphics for data analysis

- How to install: `install.packages("ggplot2")`
- First steps. Three key components:
 - Data
 - Aesthetic mappings between variables
 - At 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

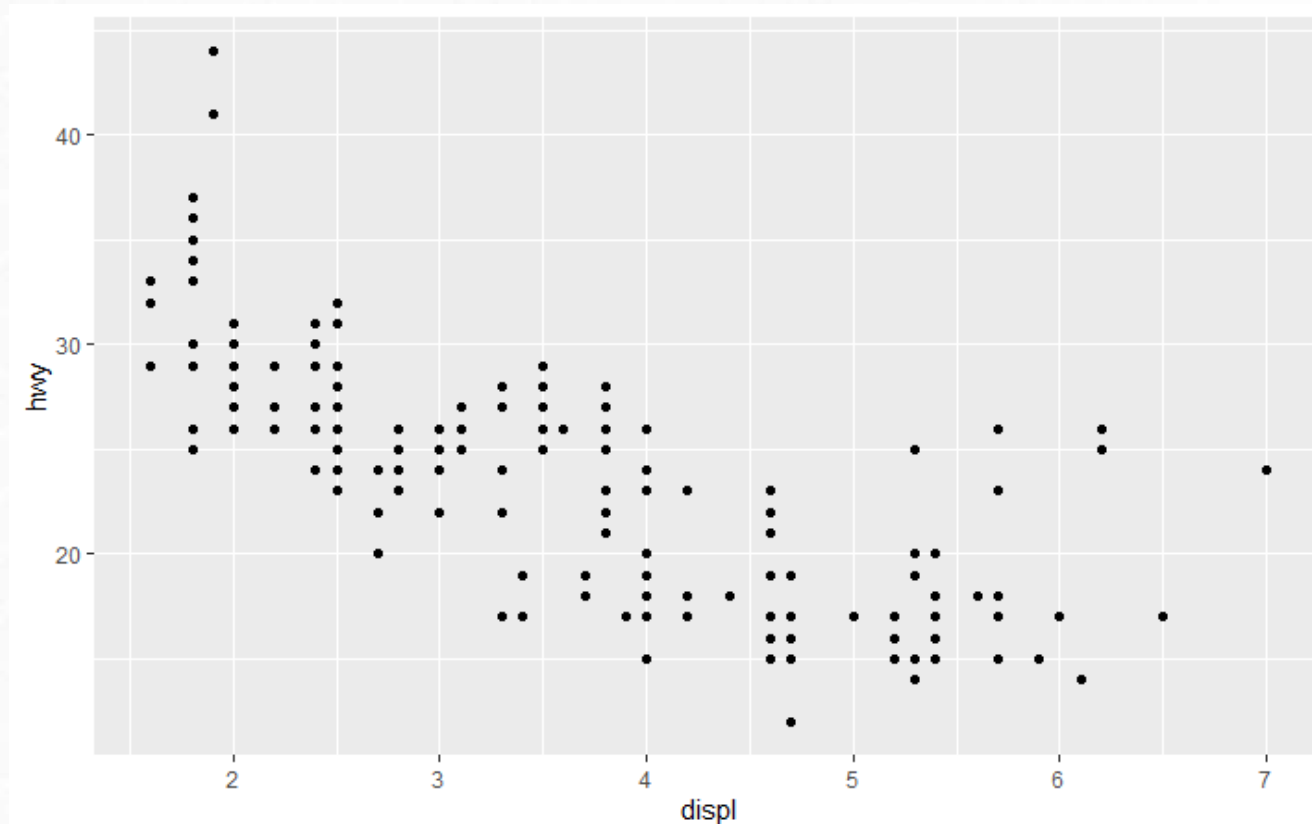
fl: fuel type

class

1. Elegant graphics for data analysis

- The basic plot:

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

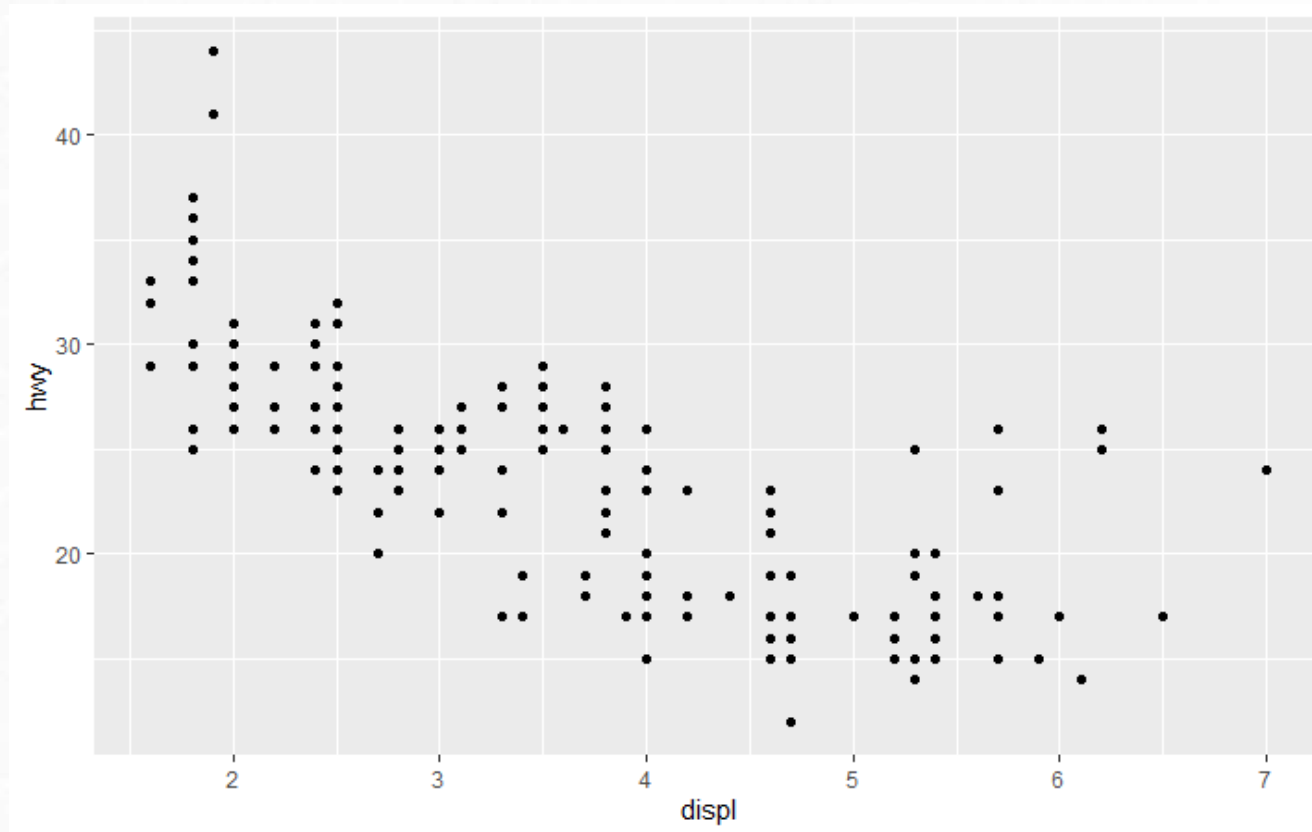


1. Elegant graphics for data analysis

- Note that it can be assigned to an R object

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

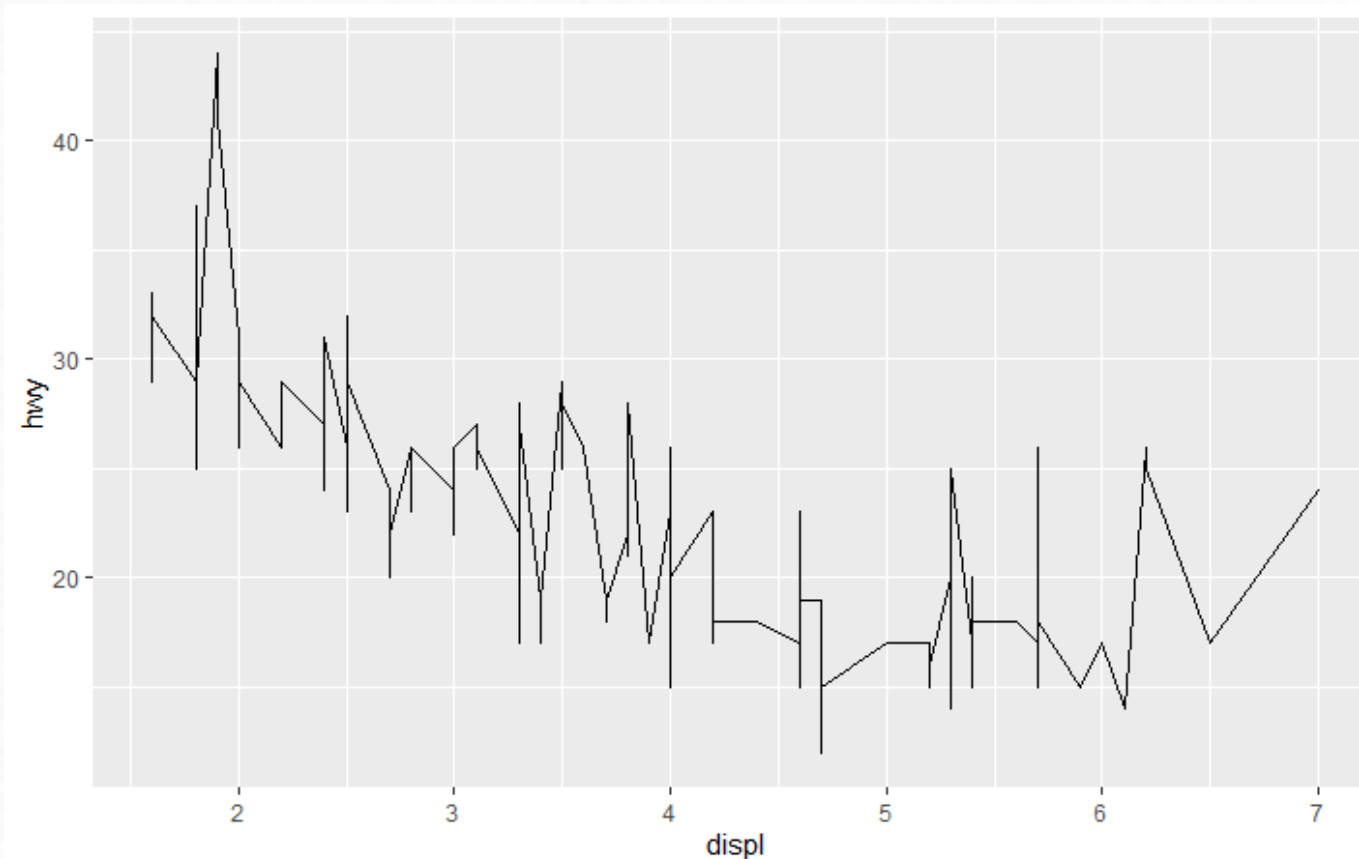
p



1. Elegant graphics for data analysis

- Playing with geoms

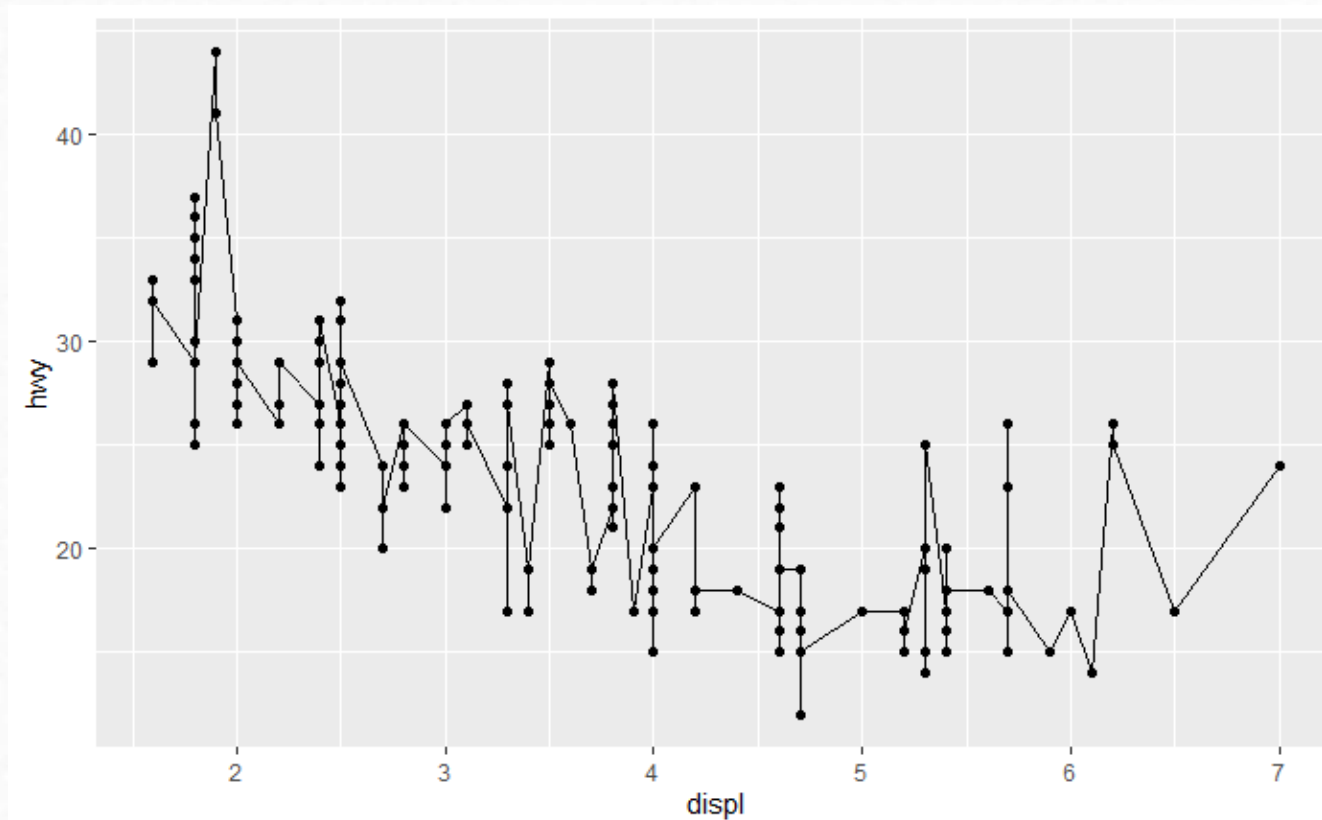
```
ggplot(mpg, aes(x = displ, y = hwy)) +  
  geom_line()
```



1. Elegant graphics for data analysis

- Adding layers

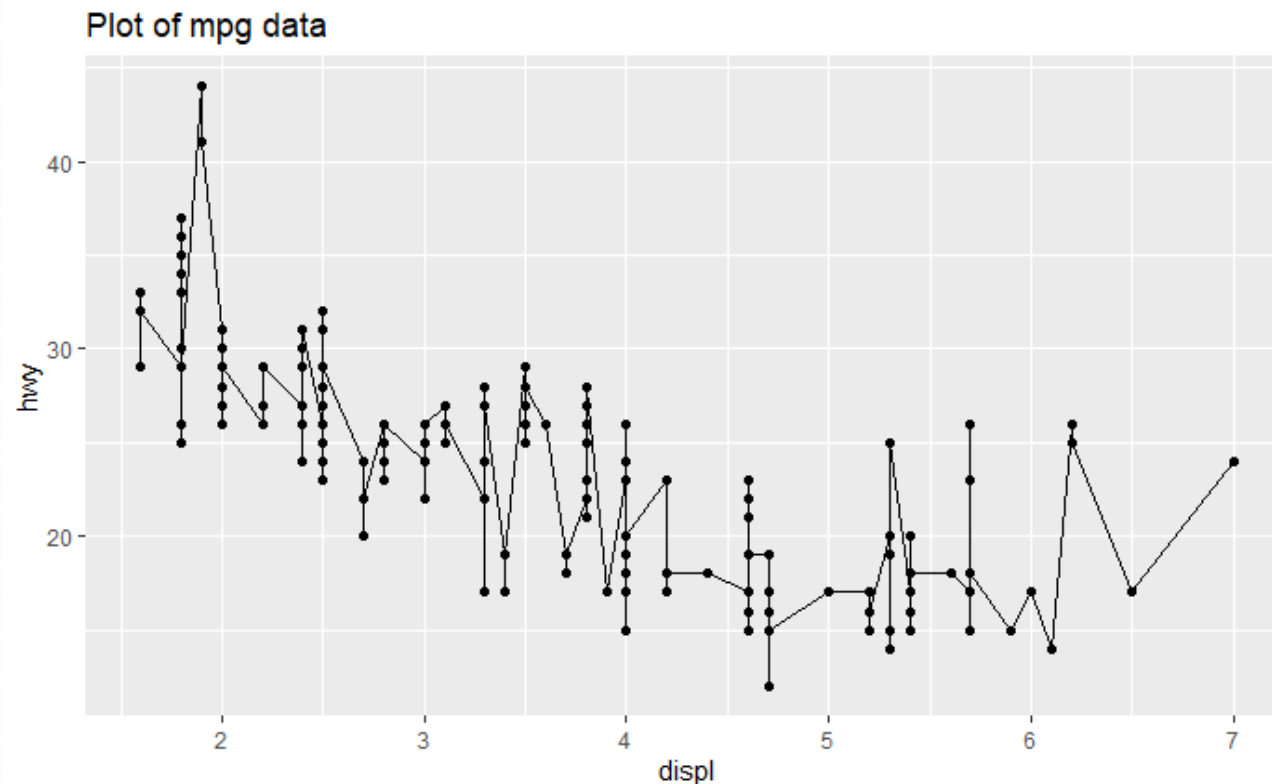
```
ggplot(mpg, aes(x = displ, y = hwy)) +  
  geom_points() +  
  geom_lines()
```



1. Elegant graphics for data analysis

- Adding layers: title

```
ggplot(mpg, aes(x = displ, y = hwy)) +  
  geom_points() +  
  geom_lines() +  
  labs(title="Plot of mpg data")
```

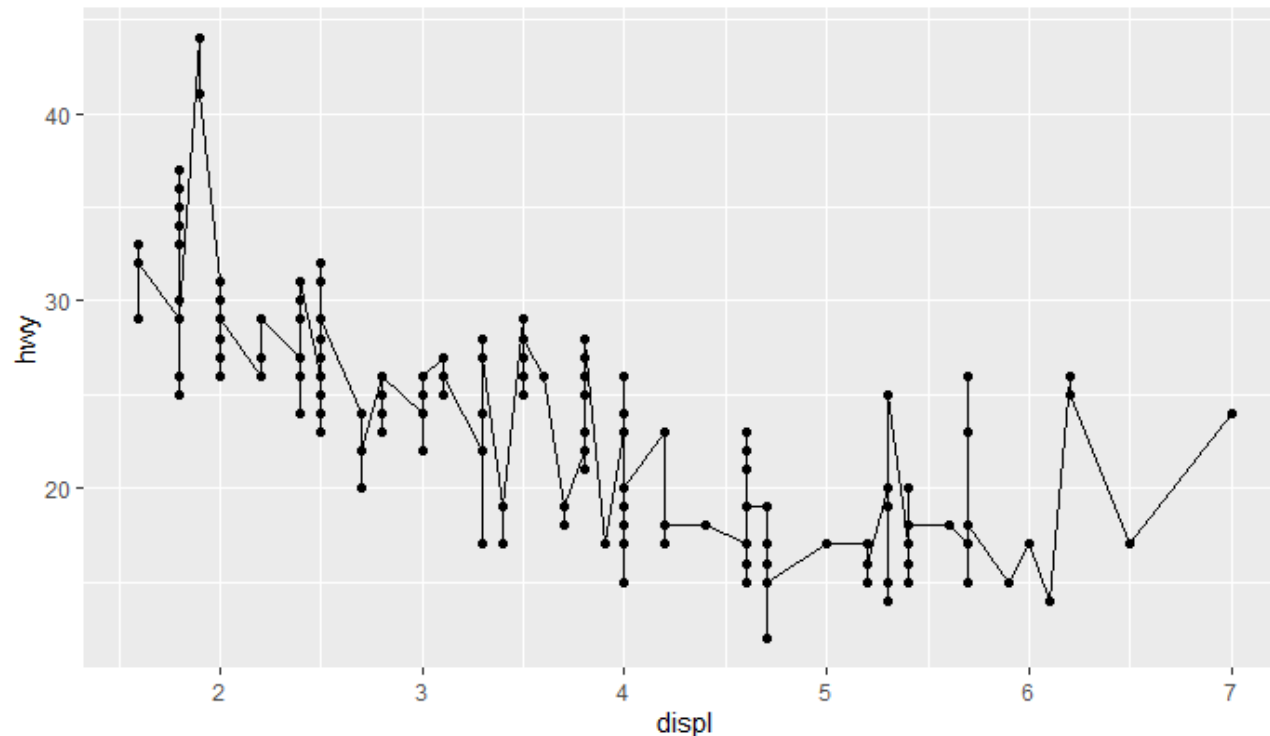


1. Elegant graphics for data analysis

- Adding layers: title

```
ggplot(mpg, aes(x = displ, y = hwy)) +  
  geom_points() +  
  geom_lines() +  
  labs(title="Plot of mpg data")
```

Plot of mpg data

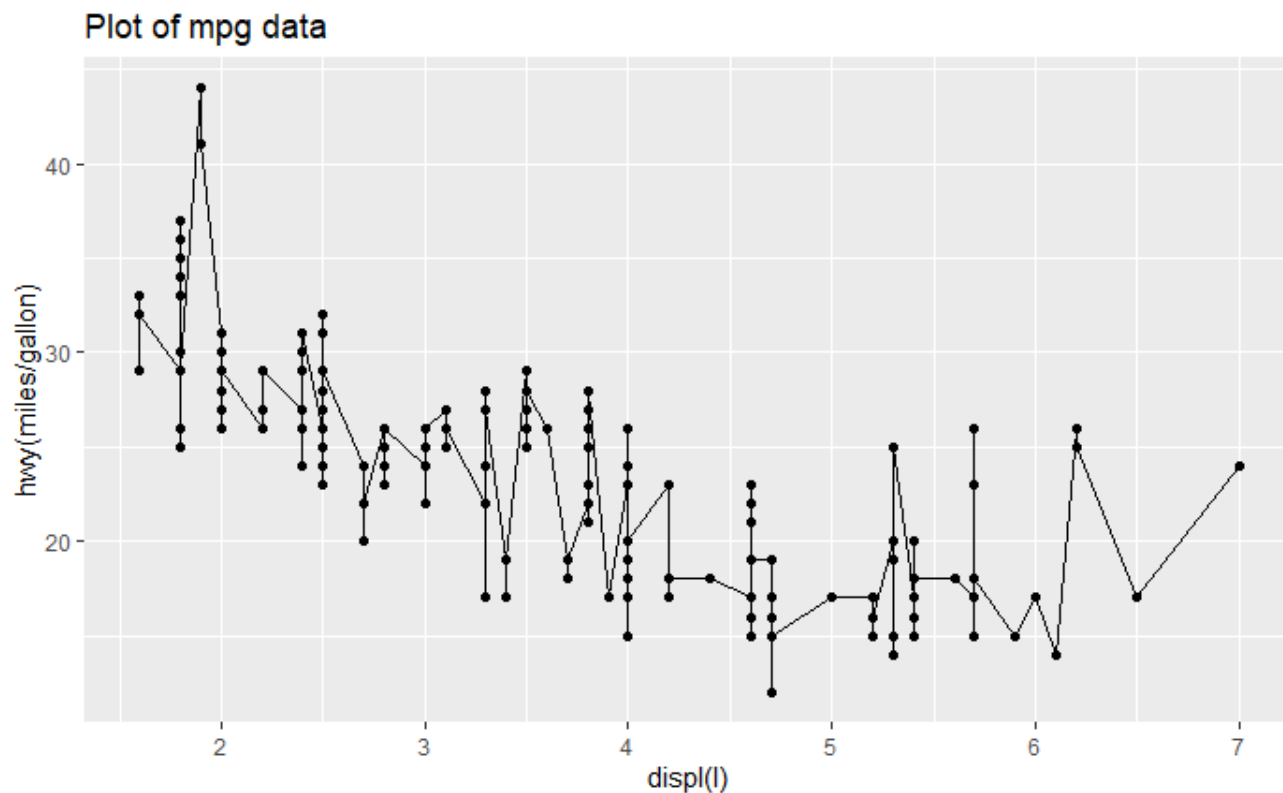


Format problems in R
when copy+paste

1. Elegant graphics for data analysis

- Changing x, y labels

```
ggplot(mpg, aes(x = displ, y = hwy)) +  
  geom_points() +  
  geom_lines() +  
  labs(title="Plot of mpg data", x="displ(l)", y="hwy(miles/gallon)")
```



1. Elegant graphics for data analysis

- Formatting labels

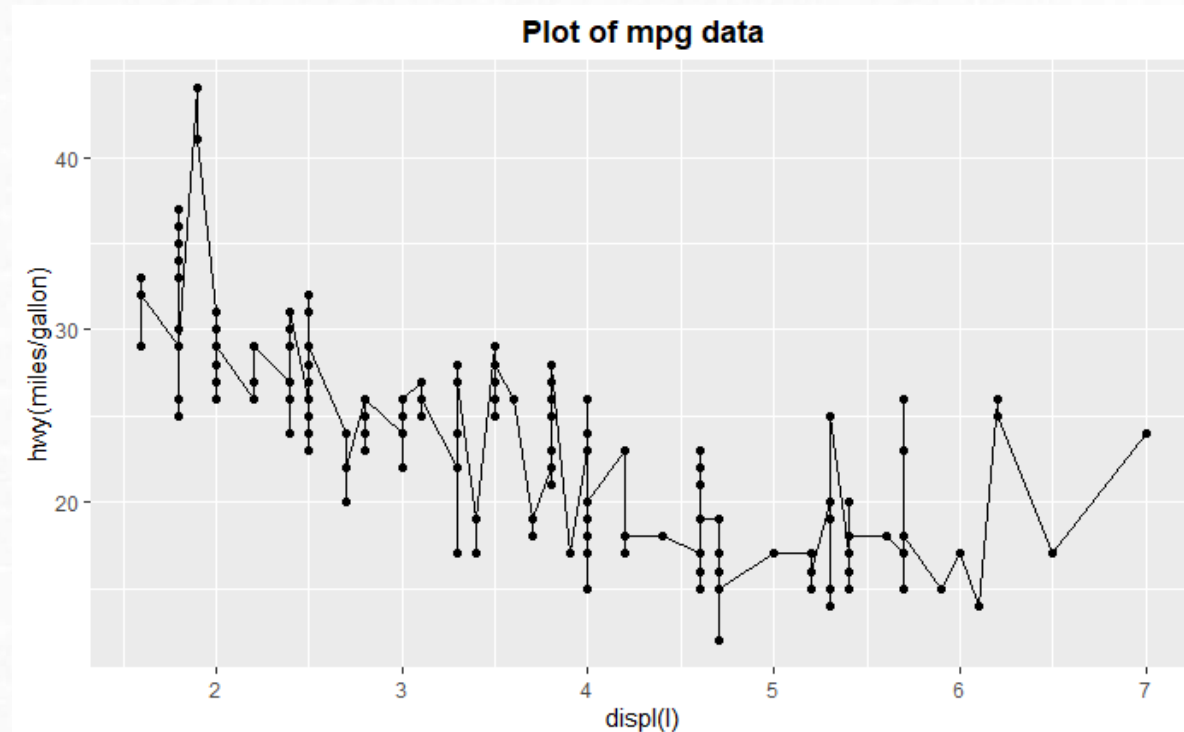
```
ggplot(mpg, aes(x = displ, y = hwy)) +  
  geom_points() +  
  geom_lines() +  
  labs(title="Plot of mpg data") +  
  theme(plot.title=element_text(face="bold", hjust=0.5))
```

- **family** : font family
- **face** : font face. Possible values are "plain", "italic", "bold" and "bold.italic"
- **colour** : text color
- **size** : text size in pts
- **hjust** : horizontal justification (in [0, 1])
- **vjust** : vertical justification (in [0, 1])
- **lineheight** : line height. In multi-line text, the *lineheight* argument is used to change the spacing between lines.
- **color** : an alias for colour

1. Elegant graphics for data analysis

- Formatting labels

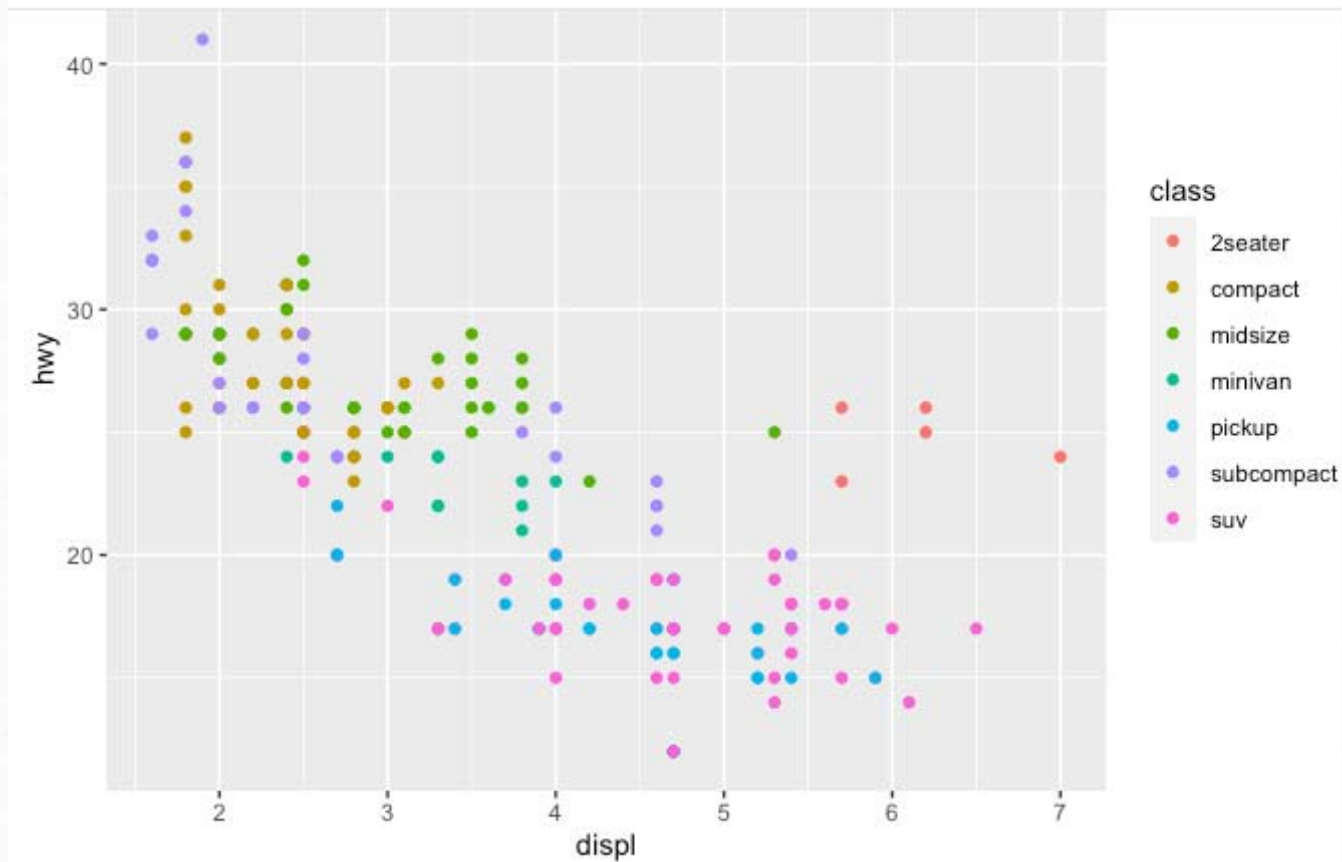
```
ggplot(mpg, aes(x = displ, y = hwy)) +  
  geom_points() +  
  geom_lines() +  
  labs(title="Plot of mpg data") +  
  theme(plot.title=element_text(face="bold", hjust=0.5))
```



1. Elegant graphics for data analysis

- Playing with aes

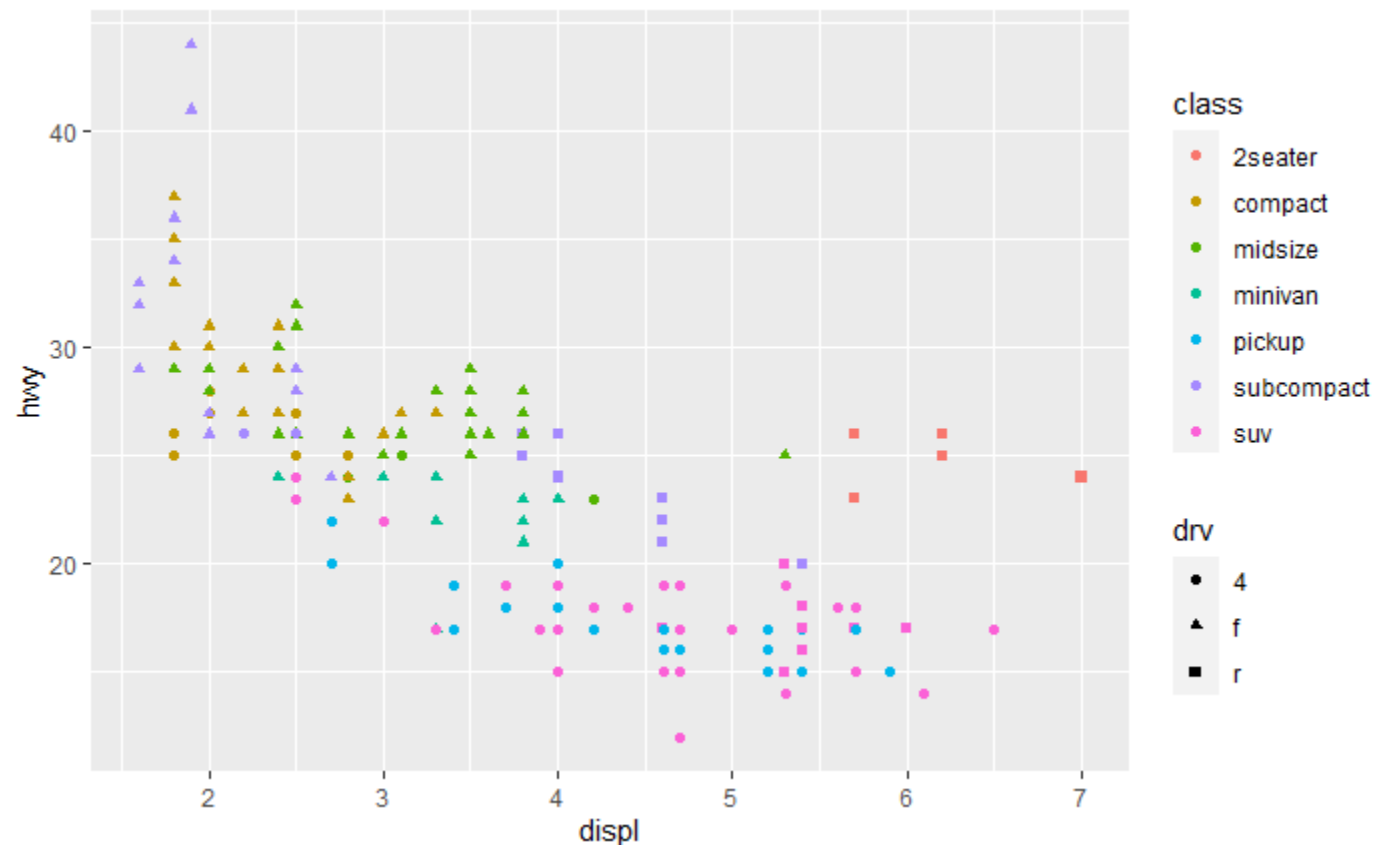
```
ggplot(mpg, aes(x = displ, y = hwy, color=class)) +  
  geom_point()
```



1. Elegant graphics for data analysis

- Playing with aes

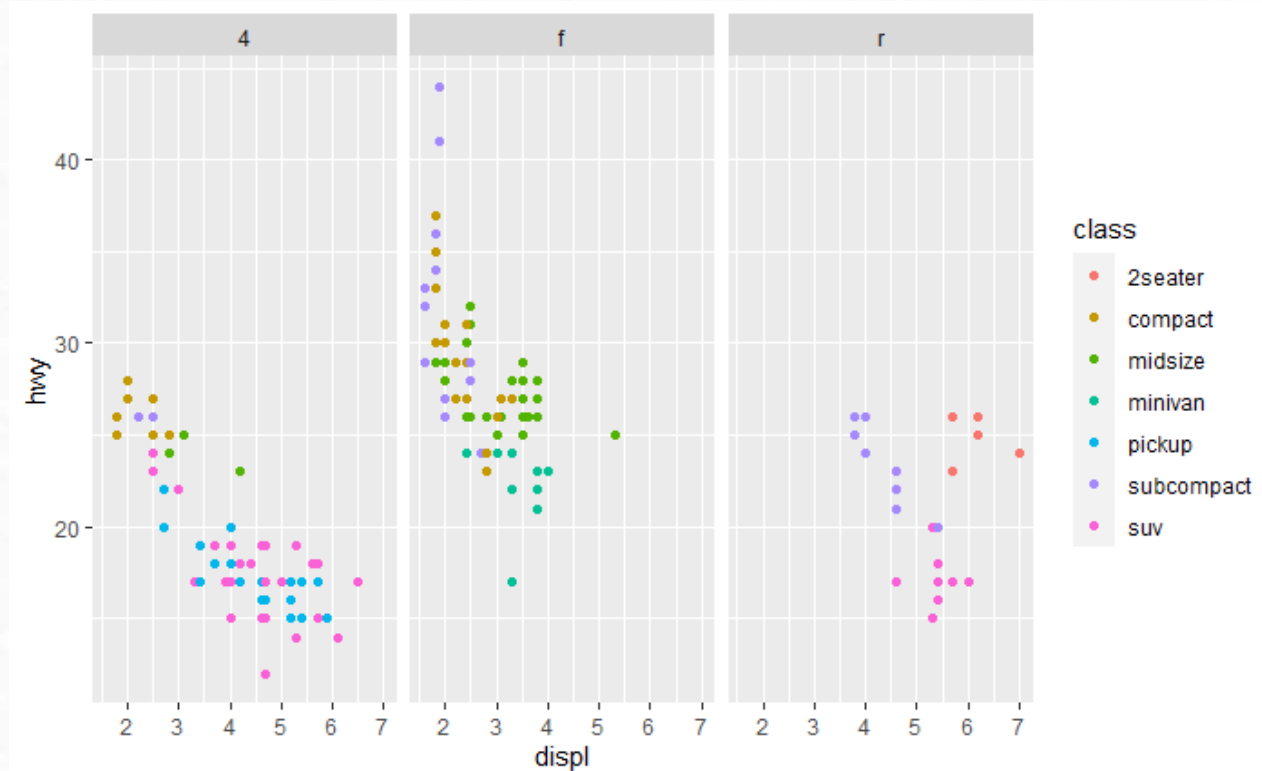
```
ggplot(mpg, aes(x = displ, y = hwy, color=class, shape=drv))+  
  geom_point()
```



1. Elegant graphics for data analysis

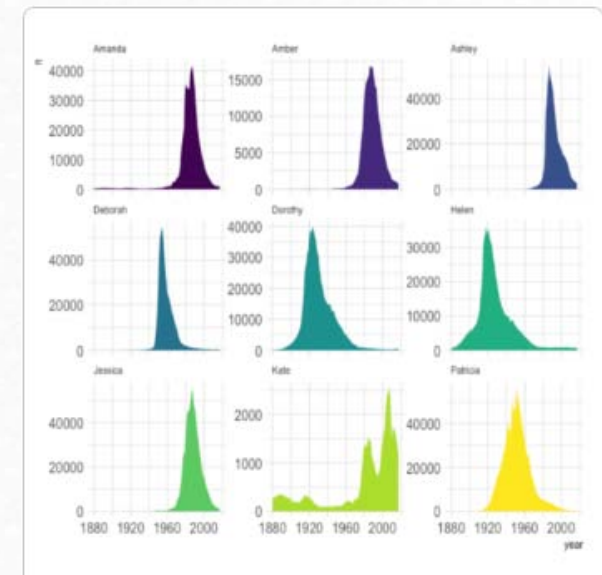
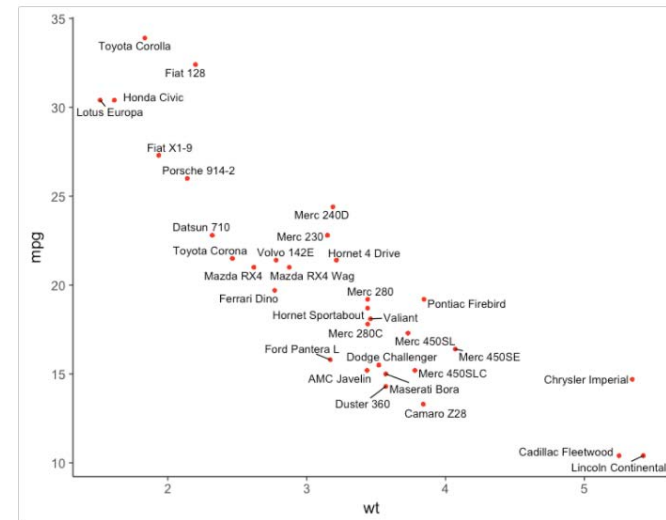
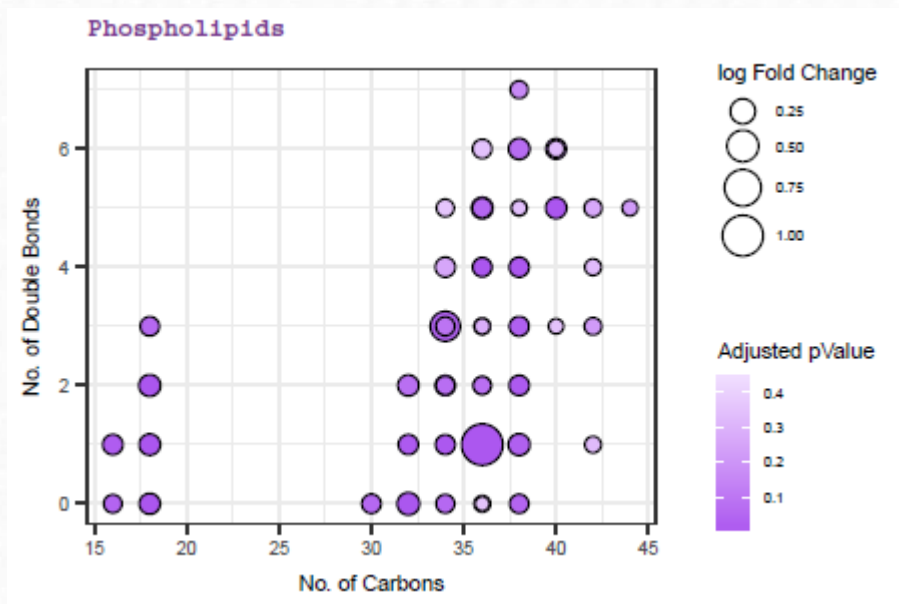
- Facets

```
ggplot(mpg, aes(x = displ, y = hwy, color=class)) +  
  geom_point() +  
  facet_grid(. ~ drv)
```



1. Elegant graphics for data analysis

And many more options



<http://www.sthda.com/english/wiki/ggplot2-essentials>
<https://www.r-graph-gallery.com/ggplot2-package.html#LogoMenu>

- Extensions to ggplot2
 - GGally, ggrepel, ...

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2. From univariate to Bivariate analysis

Last week we learned...

- We can analyse and describe each variable one by one, using graphs or numeric summaries.
- Type of graph / summary will depend on variable type

Type of variable	Numeric summary	Graphs
Quantitative	Mean, median, sd, ...	Histogram, boxplot, ..
Qualitative	Frequency tables	Barplot, pie chart, ..

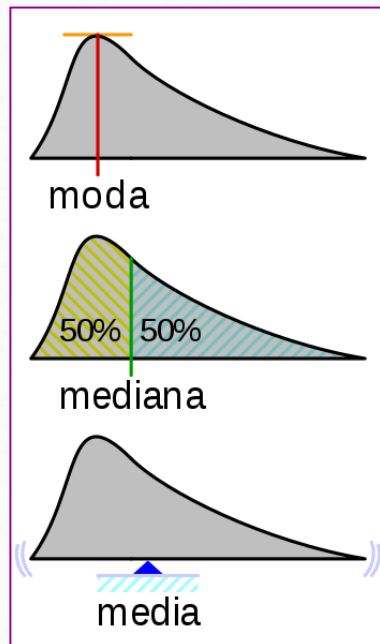
2. From univariate to Bivariate analysis

Last week we learned...

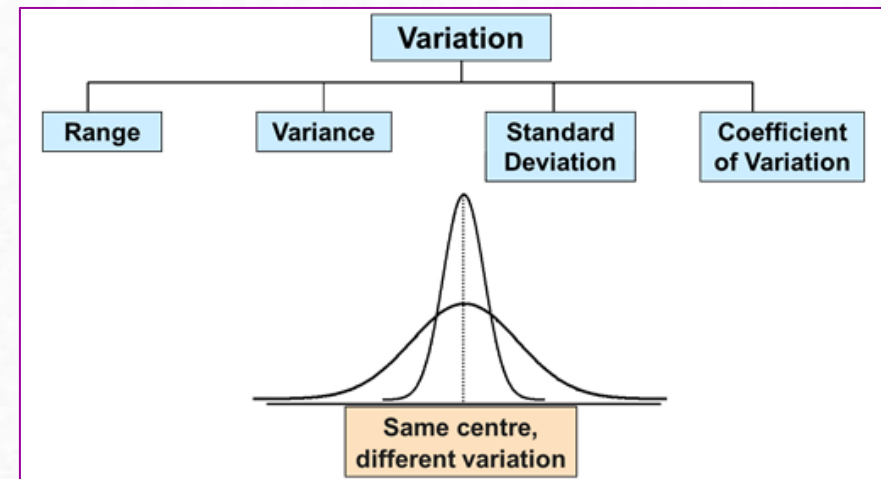
- Descriptive statistics for QUANTITATIVE VARIABLES

▣ Numeric summaries

Measures of central tendency



Measures of dispersion



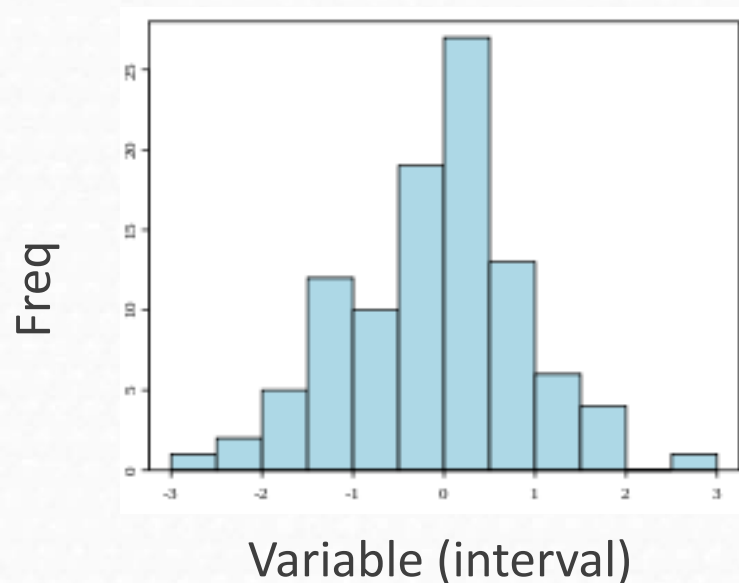
2. From univariate to Bivariate analysis

Last week we learned...

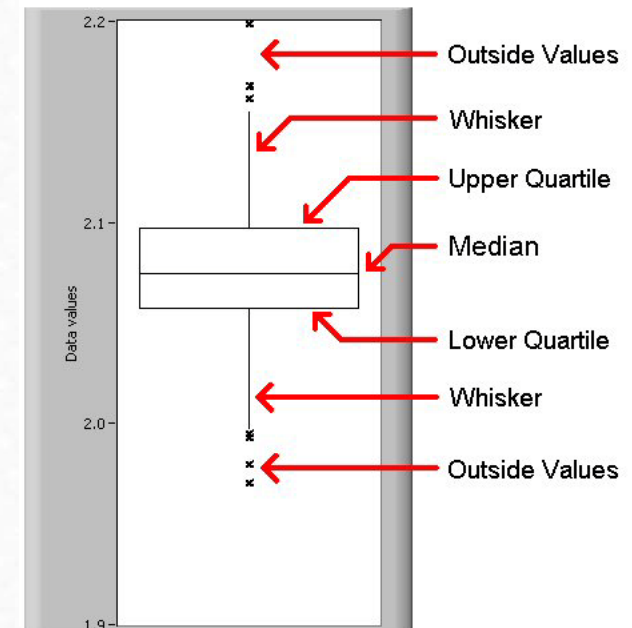
- Descriptive statistics for QUANTITATIVE VARIABLES

☐ Graphics:

Histogram



Boxplot



2. From univariate to Bivariate analysis

Last week we learned...

- Descriptive statistics for QUANTITATIVE VARIABLES

Let's do it in R!

```
# plots with basic R  
hist(mpg$displ)  
boxplot(mpg$displ)
```

```
# with ggplot2  
...
```

2. From univariate to Bivariate analysis

Last week we learned...

- Descriptive statistics for QUALITATIVE VARIABLES

☐ Numeric summaries

Frequency tables

NÚMERO DE HIJOS	Frecuencia Absoluta (f_i)	Frecuencia Relativa (fr_i)	Frecuencia Acumulada (F_i)	Frecuencia Relativa Acumulada (Fr_i)
0	175	0'35	175	0'35
1	225	0'45	400	0'80
2	75	0'15	475	0'95
3 o más	25	0'05	500	1'00
TOTAL	500	1'00	500	1'00

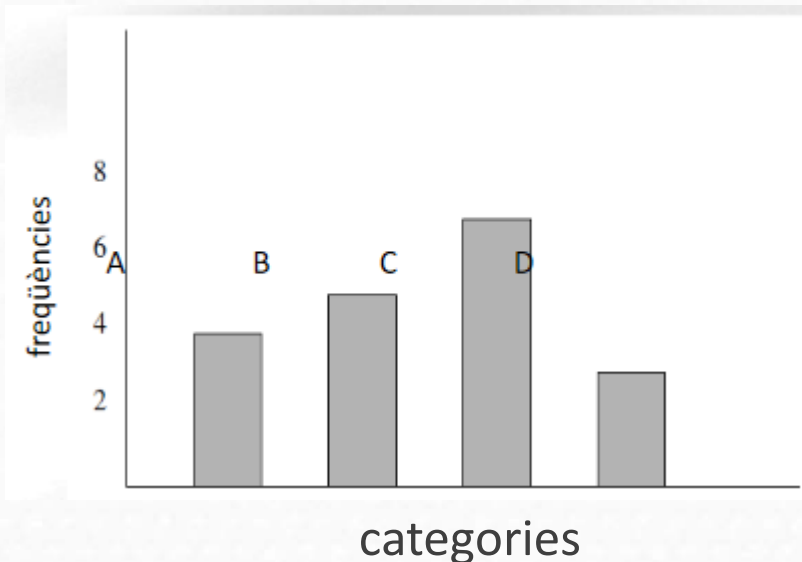
2. From univariate to Bivariate analysis

Last week we learned...

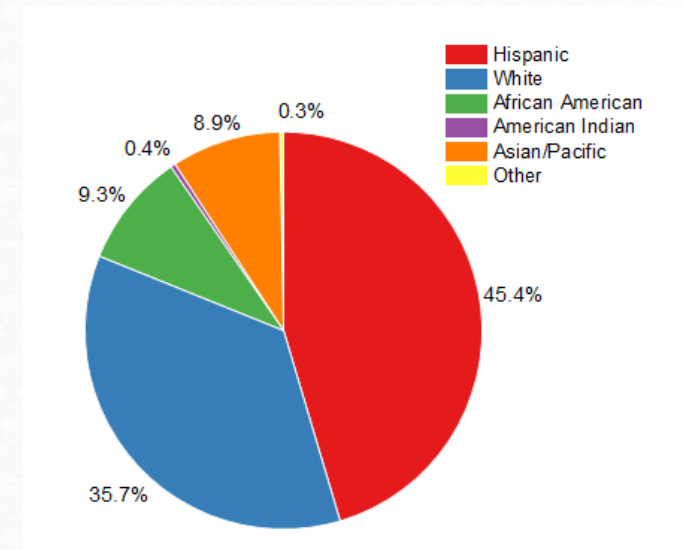
- Descriptive statistics for QUALITATIVE VARIABLES

▣ Graphics

Bar plot



Pie chart



2. From univariate to Bivariate analysis

Last week we learned...

- Descriptive statistics for QUALITATIVE VARIABLES

Let's do it in R!

```
# plots with basic R  
barplot(table(mpg$class))
```

```
# with ggplot2  
...
```

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	
30	41	10	11333692800	57	55 - 59	58.5	142.0	80	29.01210	NORMAL	

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	
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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	
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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	
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22	32	10	11287728000	59	55 - 59	101.0	156.0	82	41.50230	NORMAL	
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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	

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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 studies 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?

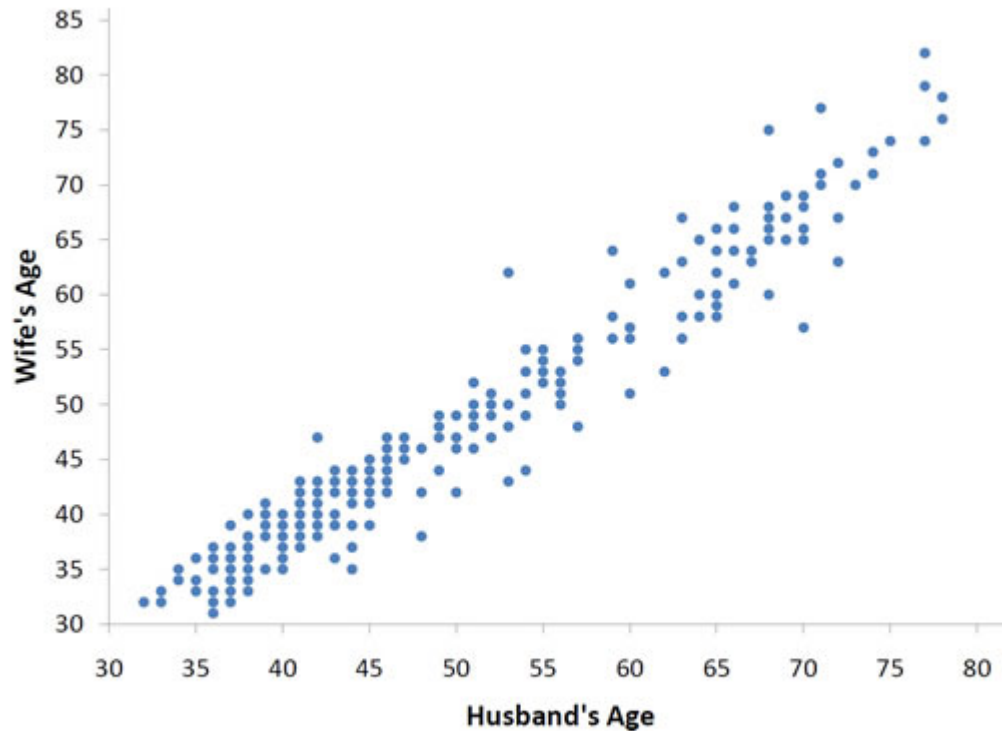
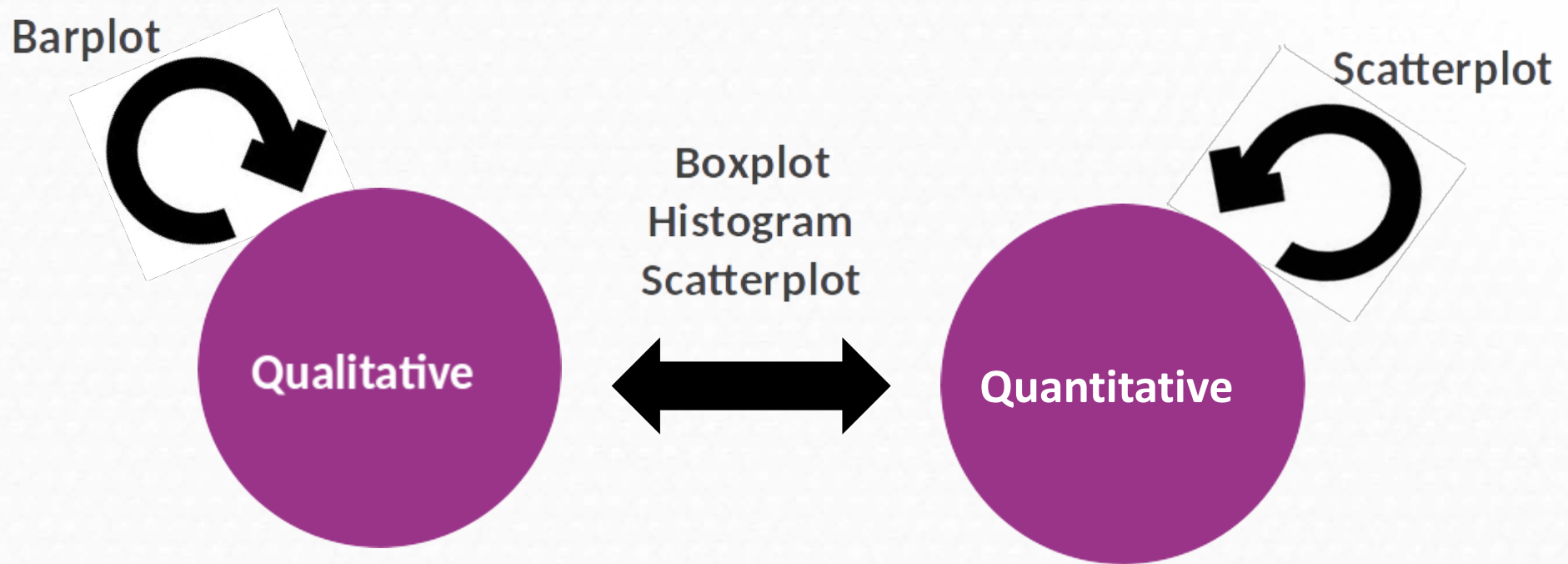


Figure 2. Scatter plot showing wife's age as a function of husband's age.

- ➡ 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...



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

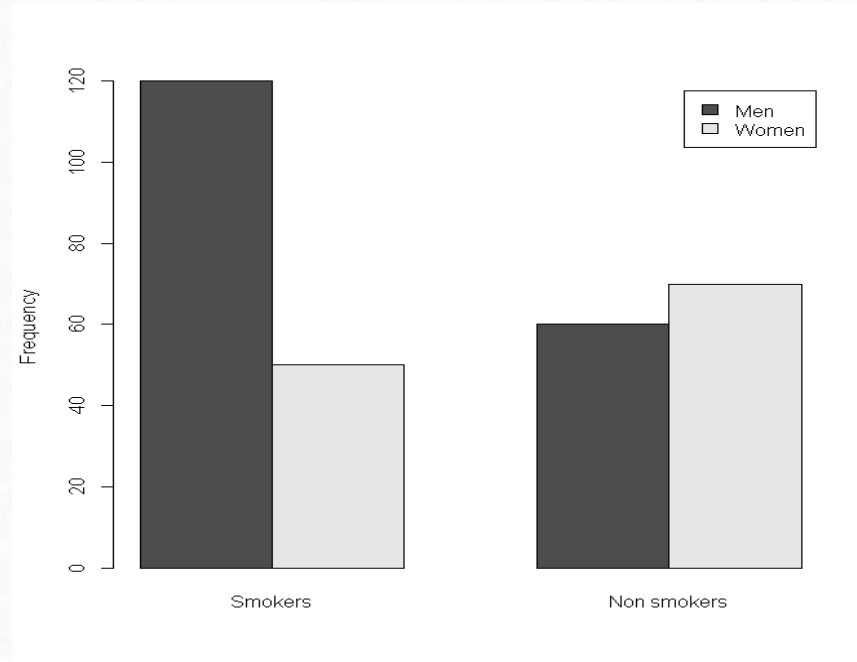
3.1 Qualitative versus qualitative

A 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

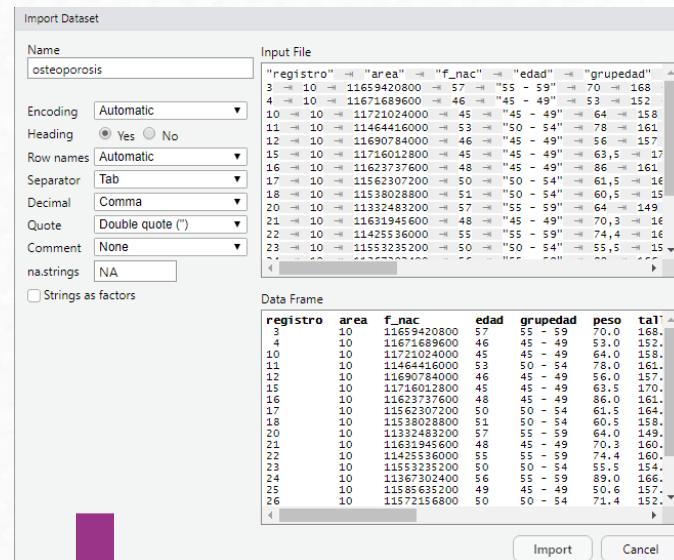
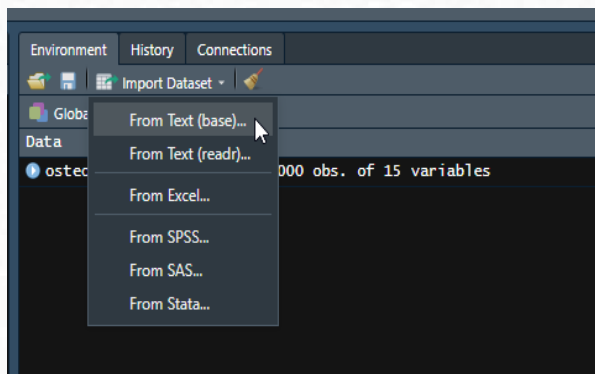


3. Bivariate analysis

3.1 Qualitative versus qualitative

Let's do it in R : Osteoporosis dataset (osteoporosis.txt)

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



A screenshot of the 'osteoporosis' dataset loaded into RStudio. The dataset is displayed in a table view with 15 columns: registro, area, f_nac, edad, grupedad, peso, talla, imc, hua, clasific, menarquia, and edad_men. The first few rows of the dataset are visible, showing patient data including age, weight, height, and classification.

registro	area	f_nac	edad	grupedad	peso	talla	imc	hua	clasific	menarquia	edad_men
3	10	11659420800	57	55 - 59	70.0	168.0	24.80	69	OSTEOPENIA	12	99
4	10	11671689600	46	45 - 49	53.0	152.0	22.94	73	OSTEOPENIA	13	99
10	10	11721024000	45	45 - 49	64.0	158.0	25.64	81	NORMAL	14	99
11	10	11464416000	53	50 - 54	78.0	161.0	30.09	58	OSTEOPENIA	10	50
12	10	11690784000	46	45 - 49	56.0	157.0	22.72	89	NORMAL	13	99
15	10	11716012800	45	45 - 49	63.5	170.0	21.97	76	NORMAL	14	99
16	10	11623737600	48	45 - 49	86.0	161.0	33.10	87	NORMAL	11	99
17	10	11562307200	50	50 - 54	61.5	164.0	22.87	74	NORMAL	10	99
18	10	11538028800	51	50 - 54	60.5	158.0	24.23	58	OSTEOPENIA	14	99
20	10	11332483200	57	55 - 59	64.0	149.0	28.83	61	OSTEOPENIA	13	50
21	10	11631945600	48	45 - 49	70.3	160.0	27.46	67	OSTEOPENIA	12	48
22	10	11425536000	55	55 - 59	74.4	160.0	29.06	68	OSTEOPENIA	14	50
23	10	11553235200	50	50 - 54	55.5	154.5	23.25	73	OSTEOPENIA	11	48
24	10	11367302400	56	55 - 59	89.0	166.0	32.30	61	OSTEOPENIA	14	47

3. Bivariate analysis

3.1 Qualitative versus qualitative

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

3.1 Qualitative versus qualitative

```
table(osteoporosis$grupedad, osteoporosis$clasific)
```

	NORMAL	OSTEOPENIA	OSTEOPOROSIS
45 - 49	233	138	7
50 - 54	113	113	7
55 - 59	67	100	9
60 - 64	38	74	17
65 - 69	18	42	24

```
prop.table(table(osteoporosis$grupedad, osteoporosis$clasific))
```

	NORMAL	OSTEOPENIA	OSTEOPOROSIS
45 - 49	0.233	0.138	0.007
50 - 54	0.113	0.113	0.007
55 - 59	0.067	0.100	0.009
60 - 64	0.038	0.074	0.017
65 - 69	0.018	0.042	0.024

3. Bivariate analysis

3.1 Qualitative versus qualitative

Another way to introduce the data:

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

```
tab <- matrix(data = c(120, 60, 50, 70), nrow = 2, ncol = 2, byrow = TRUE)
tab
```

```
      [,1] [,2]
[1,]  120   60
[2,]   50   70
```

```
colnames(tab) <- c("Smokers", "Nonsmokers")
rownames(tab) <- c("Men", "Women")
tab
```

```
      Smokers Nonsmokers
Men      120       60
Women     50       70
```


3. Bivariate analysis

3.1 Qualitative versus qualitative

Another way to introduce the data:

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

```
prop.table(tab)
```

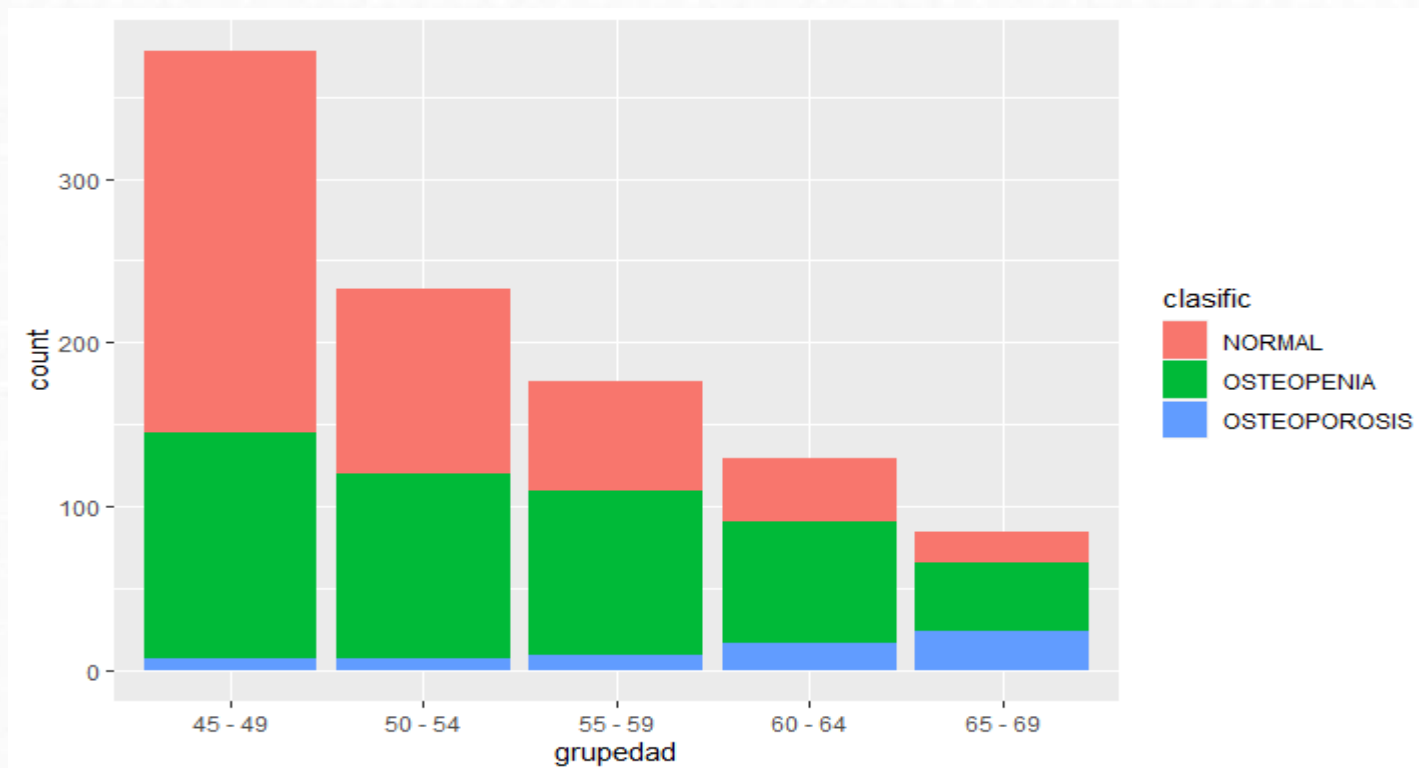
```
      Smokers Nonsmokers  
Men    0.4000000 0.2000000  
Women  0.1666667 0.2333333
```

3. Bivariate analysis

3.1 Qualitative versus qualitative

Barplot with R

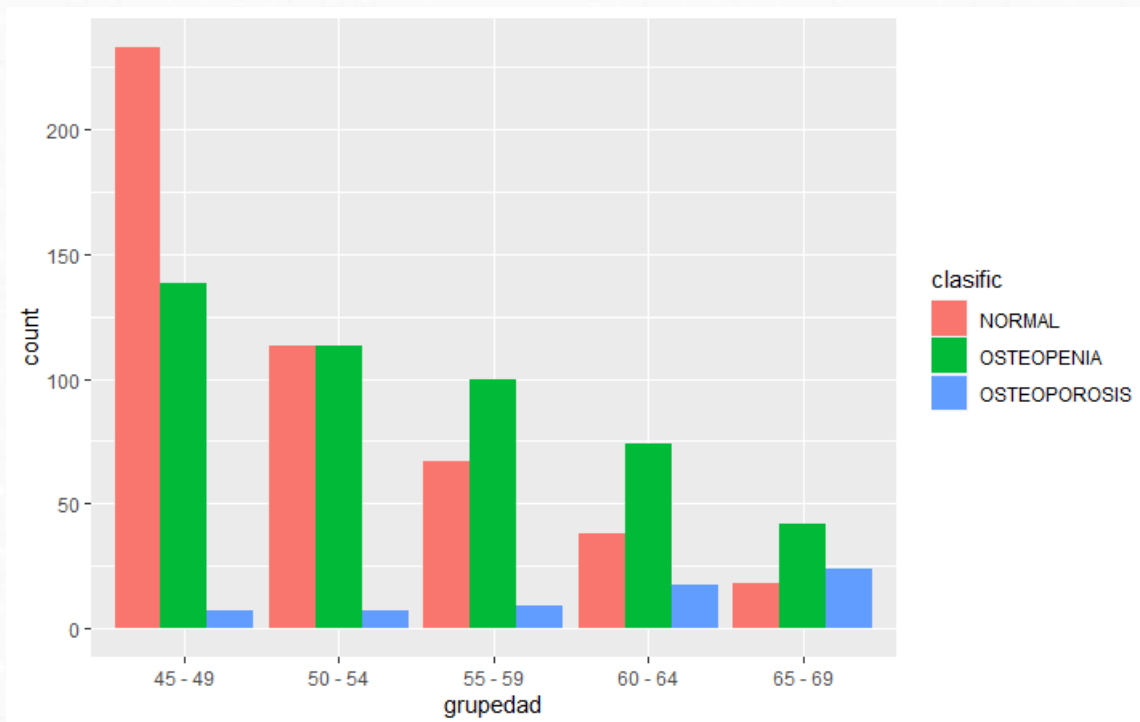
```
ggplot(data = osteoporosis, aes(x = grupedad)) +  
  geom_bar(aes(fill = clasific))
```



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>

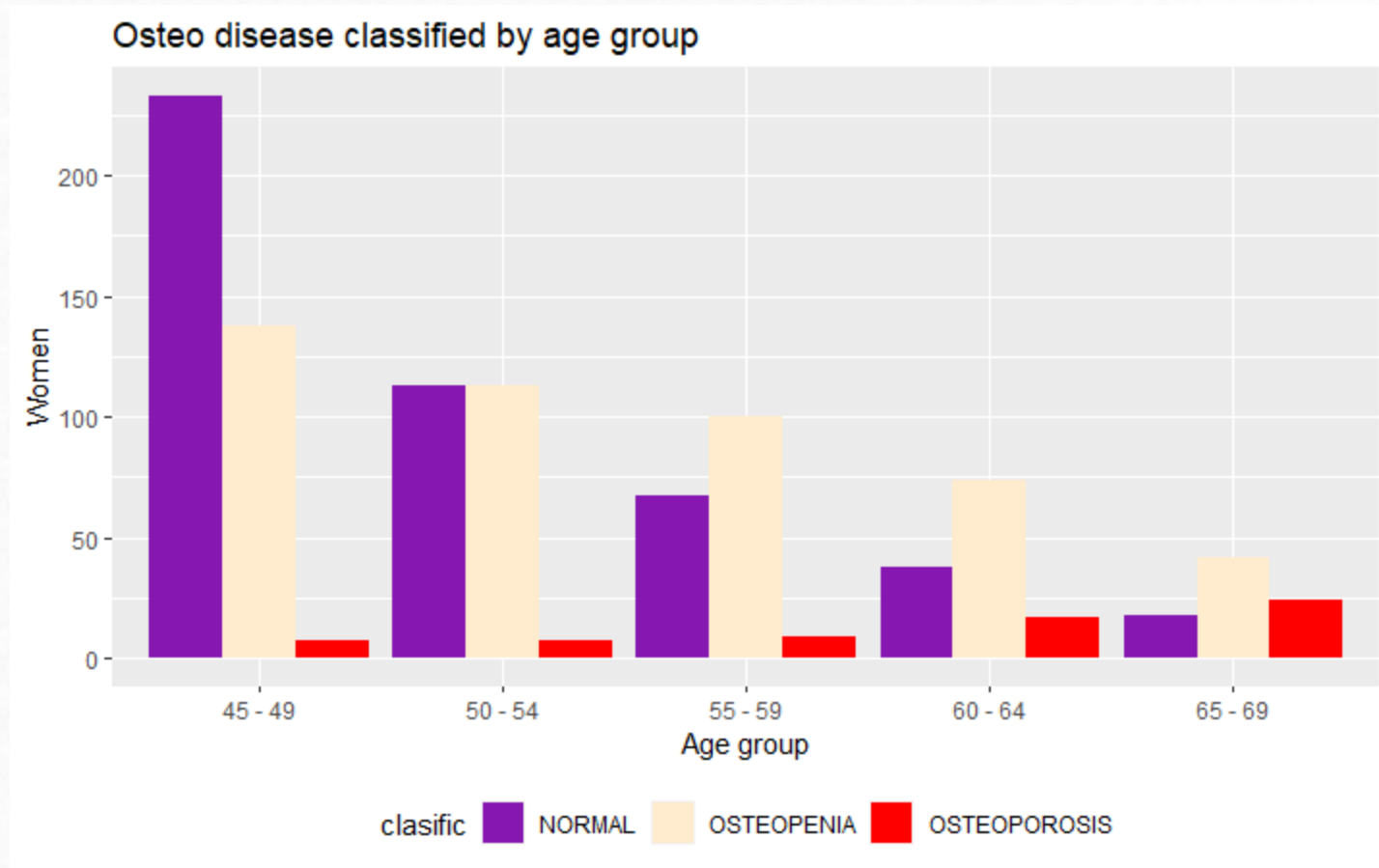
Change colors, legend position, labels and finally save it!

```
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

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

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

Let's do in R:

Osteoporosis dataset

Study if/how bone density (*bua*) changes in each group of age (*grupedad*)

```
➤ with(osteoporosis, tapply(bua, list(grupedad), mean, na.rm=TRUE))
```

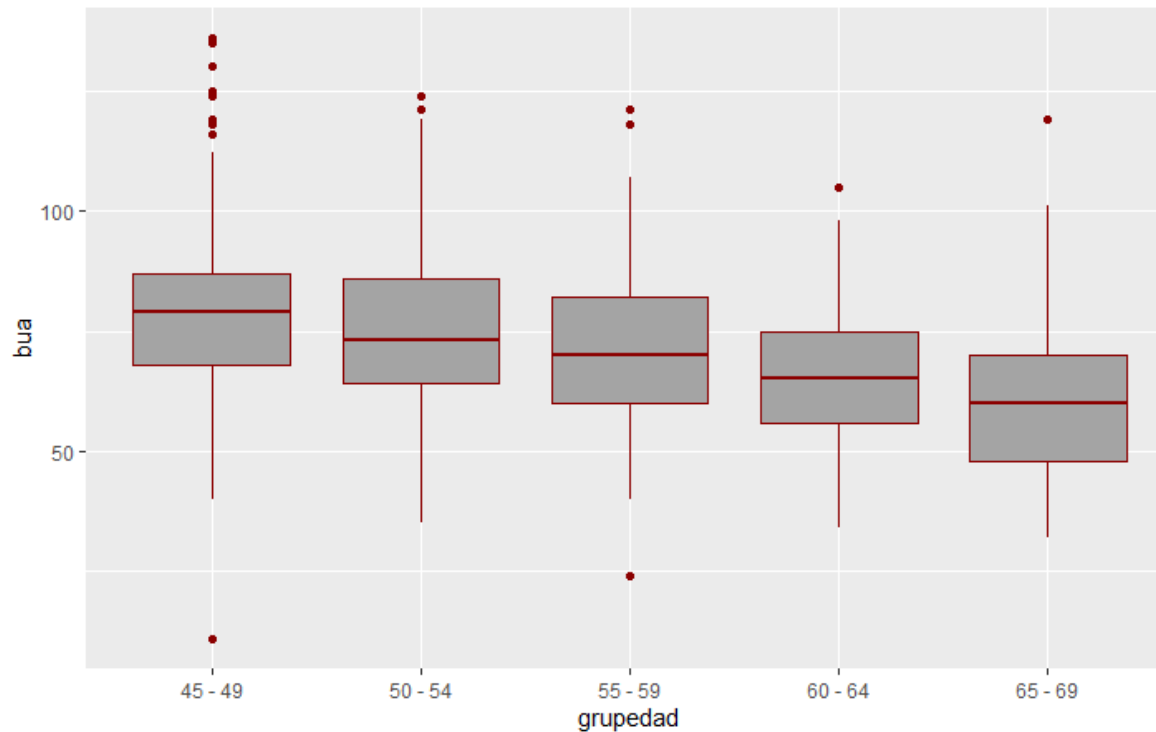
45-49	50-54	55-59	60-64	65-69
78.75926	75.05150	71.43182	64.89147	60.66667

3. Bivariate analysis

3.2 Qualitative versus quantitative

Study if bone density (*bua*) is different in each group of age

```
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 different in each group of age

```
# 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 (*clasific*)

- ☐ Type of variables?
- ☐ Type of numerical bivariate analysis?
- ☐ Type of graphical bivariate analysis?

Study if *peso* is different in each group of illness (*clasific*).

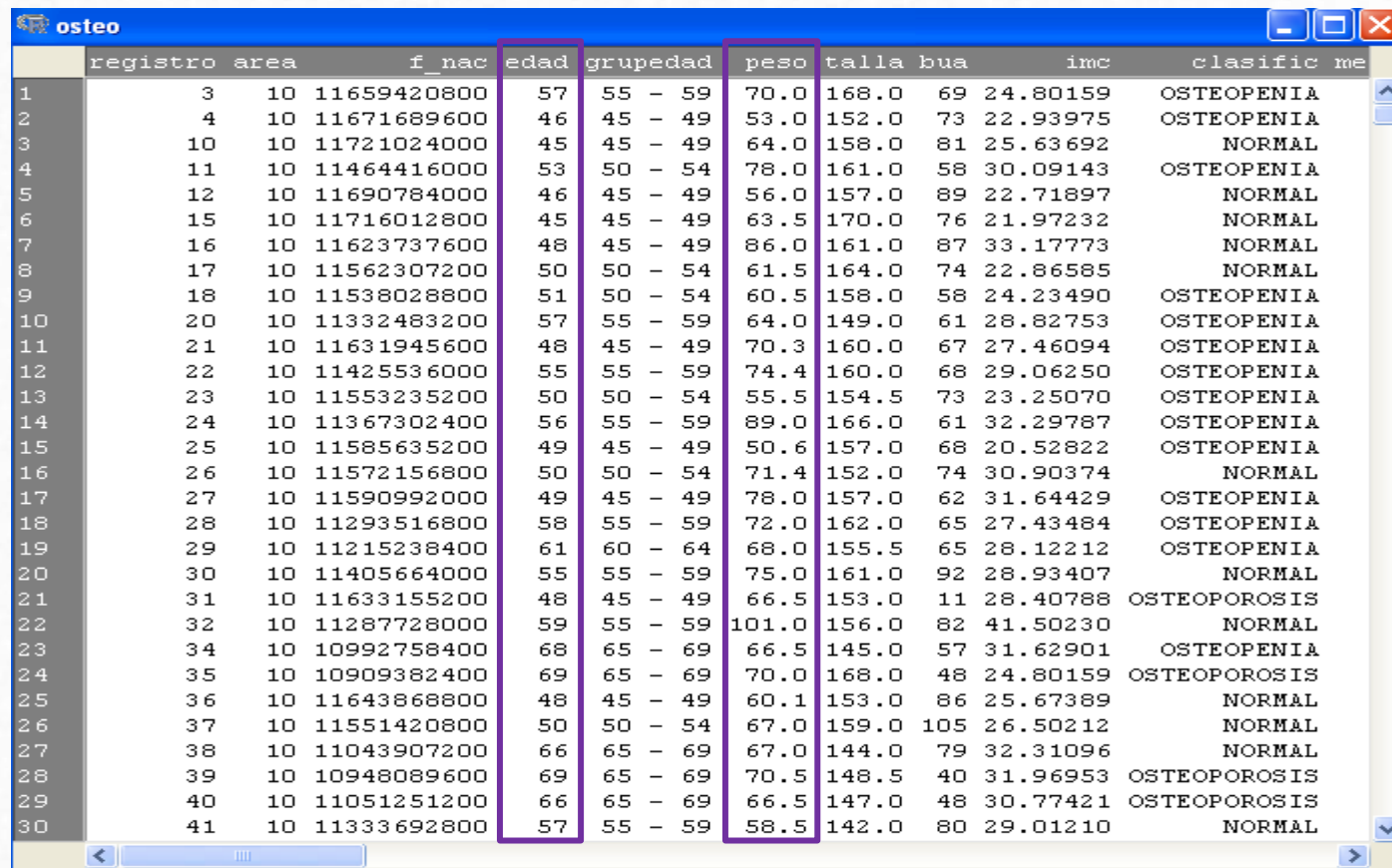
- ☐ Type of variables?
- ☐ Type of numerical bivariate analysis?
- ☐ Type of graphical bivariate analysis?

3. Bivariate analysis

3.3 Quantitative versus Quantitative

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

- Two **quantitatives** variables:



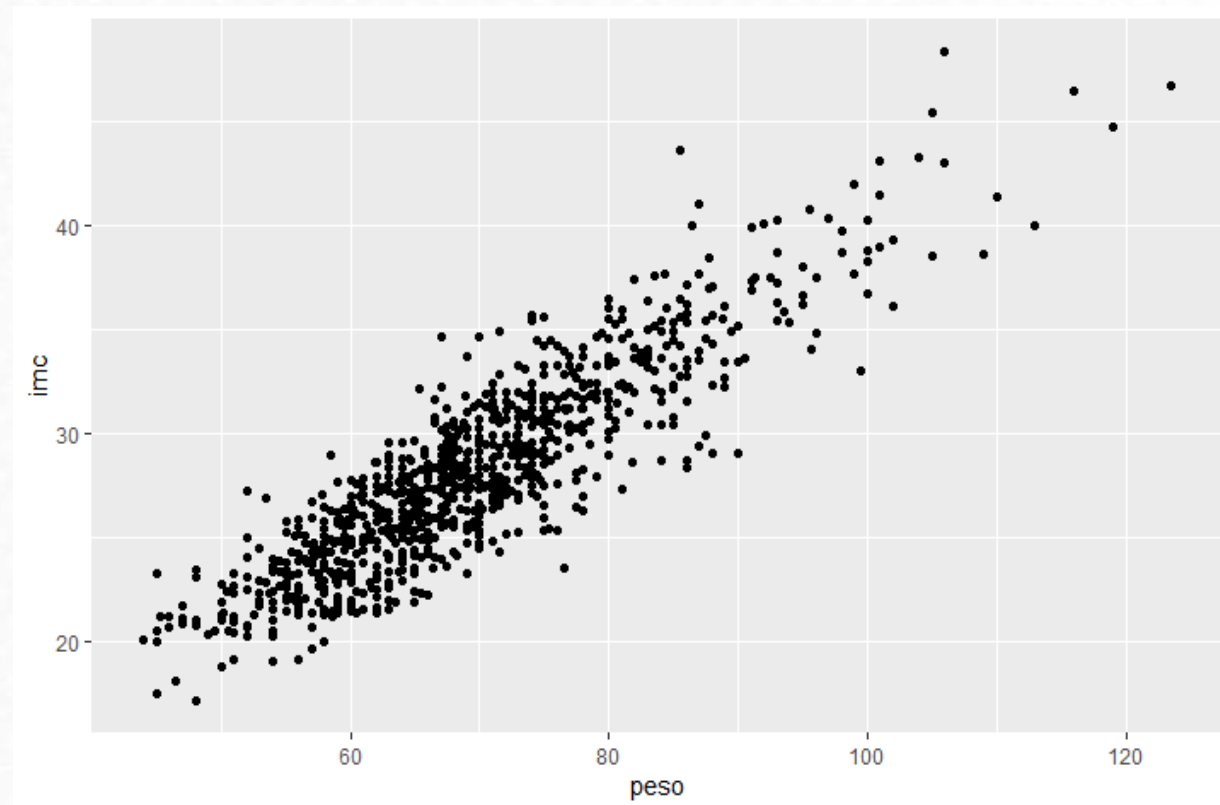
	registro	area	f_nac	edad	grupedad	peso	talla	bua	imc	clasific me
1	3	10	11659420800	57	55 - 59	70.0	168.0	69	24.80159	OSTEOPENIA
2	4	10	11671689600	46	45 - 49	53.0	152.0	73	22.93975	OSTEOPENIA
3	10	10	11721024000	45	45 - 49	64.0	158.0	81	25.63692	NORMAL
4	11	10	11464416000	53	50 - 54	78.0	161.0	58	30.09143	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

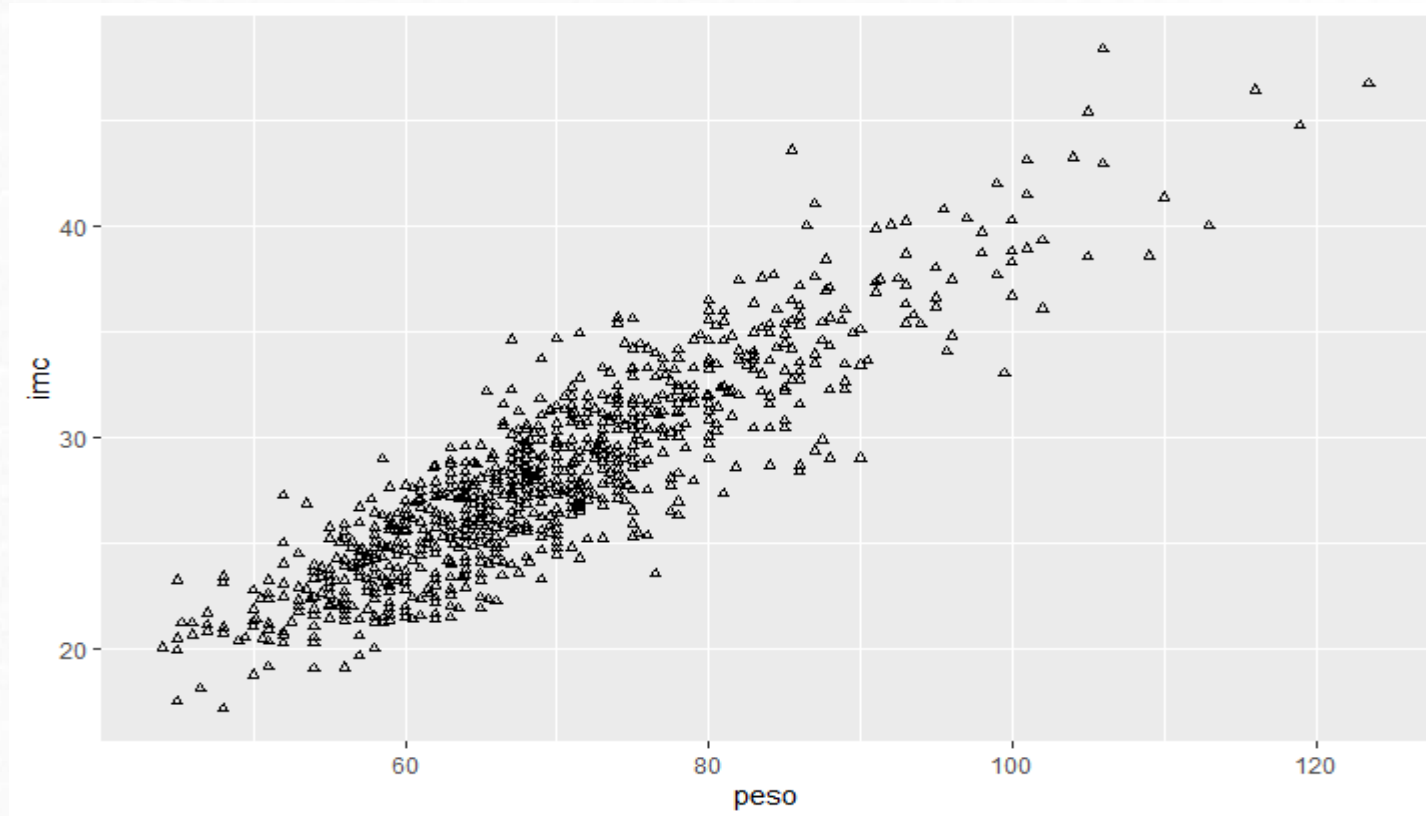
```
ggplot(osteoporosis, aes(x = peso, y = imc)) +  
  geom_point()
```



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)
```

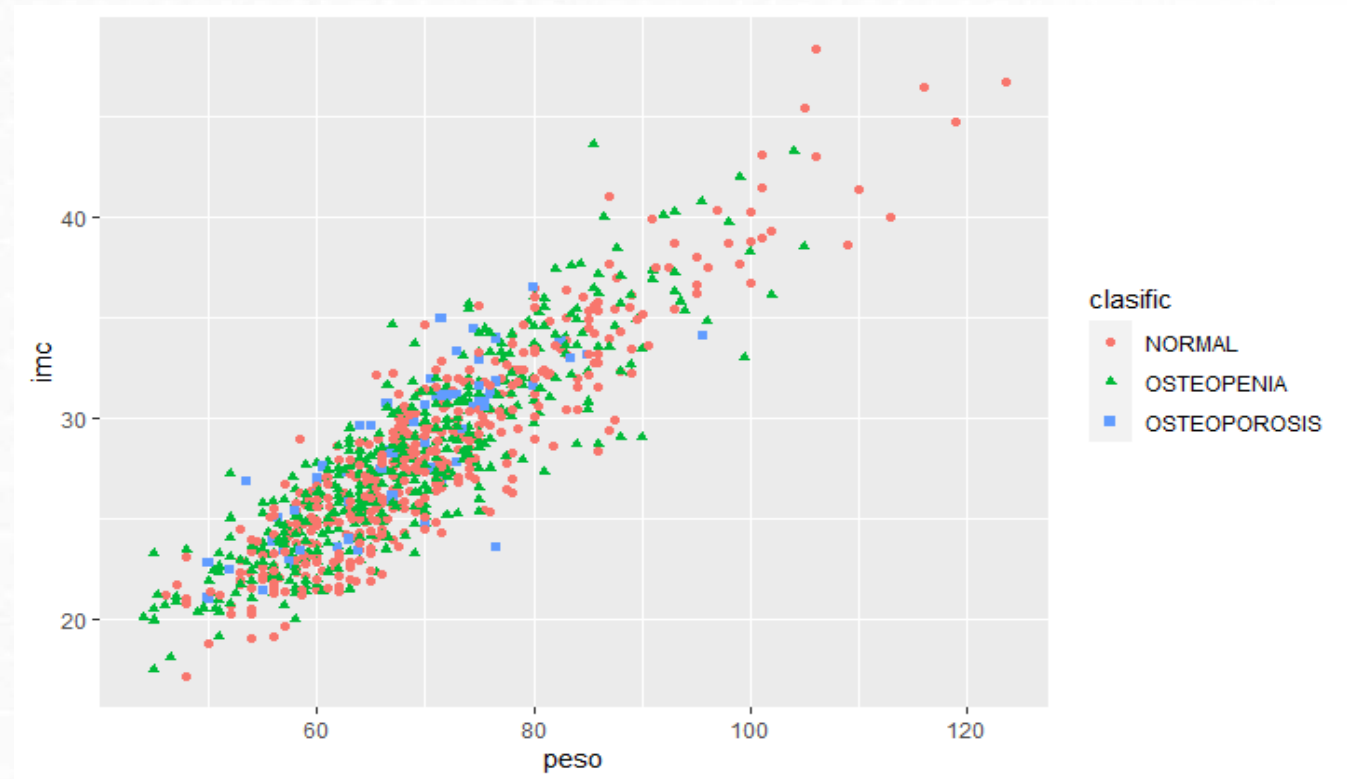


3. Bivariate analysis

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()
```

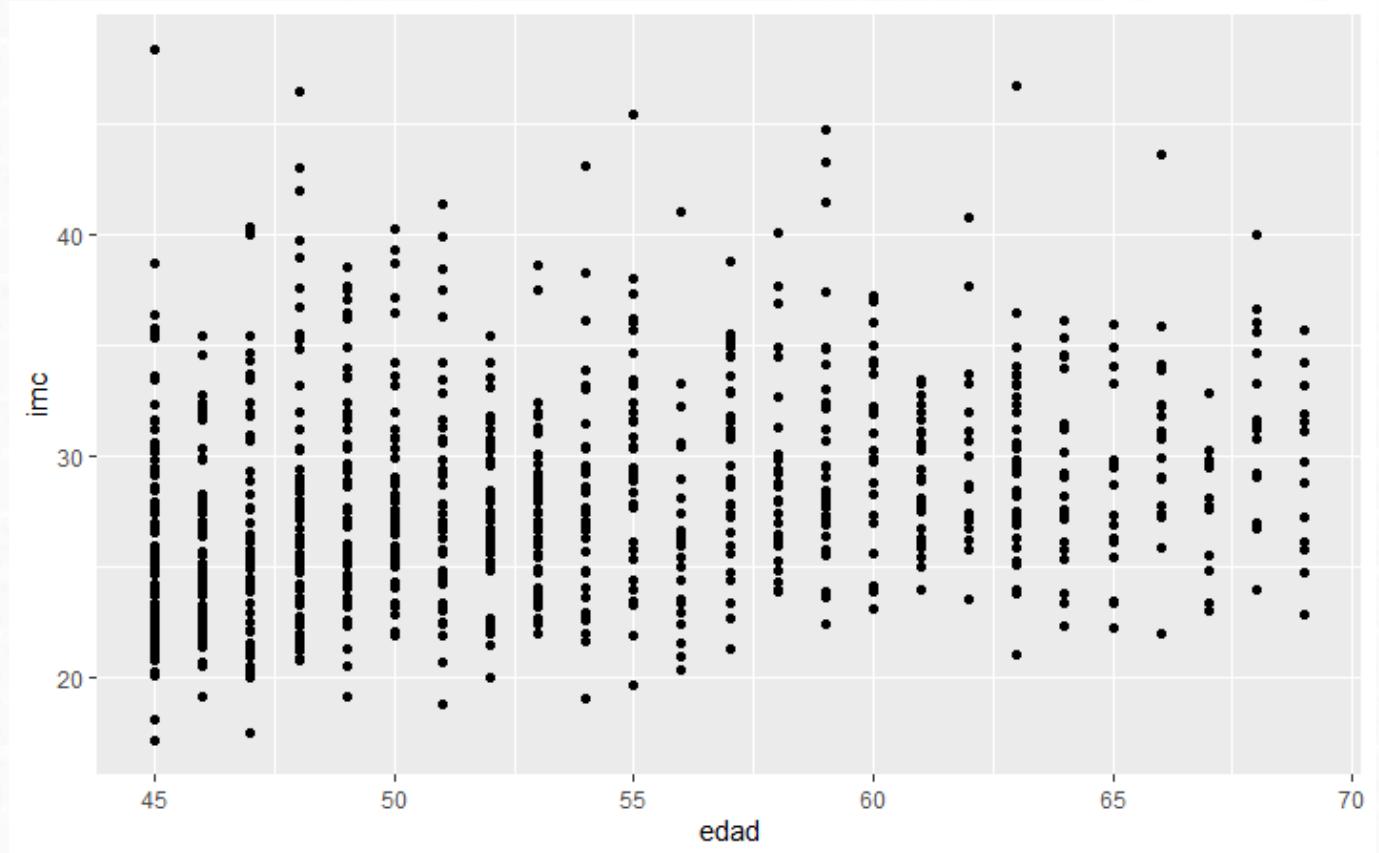


3. Bivariate analysis

3.3 Quantitative versus Quantitative

But not allways the correlation is good

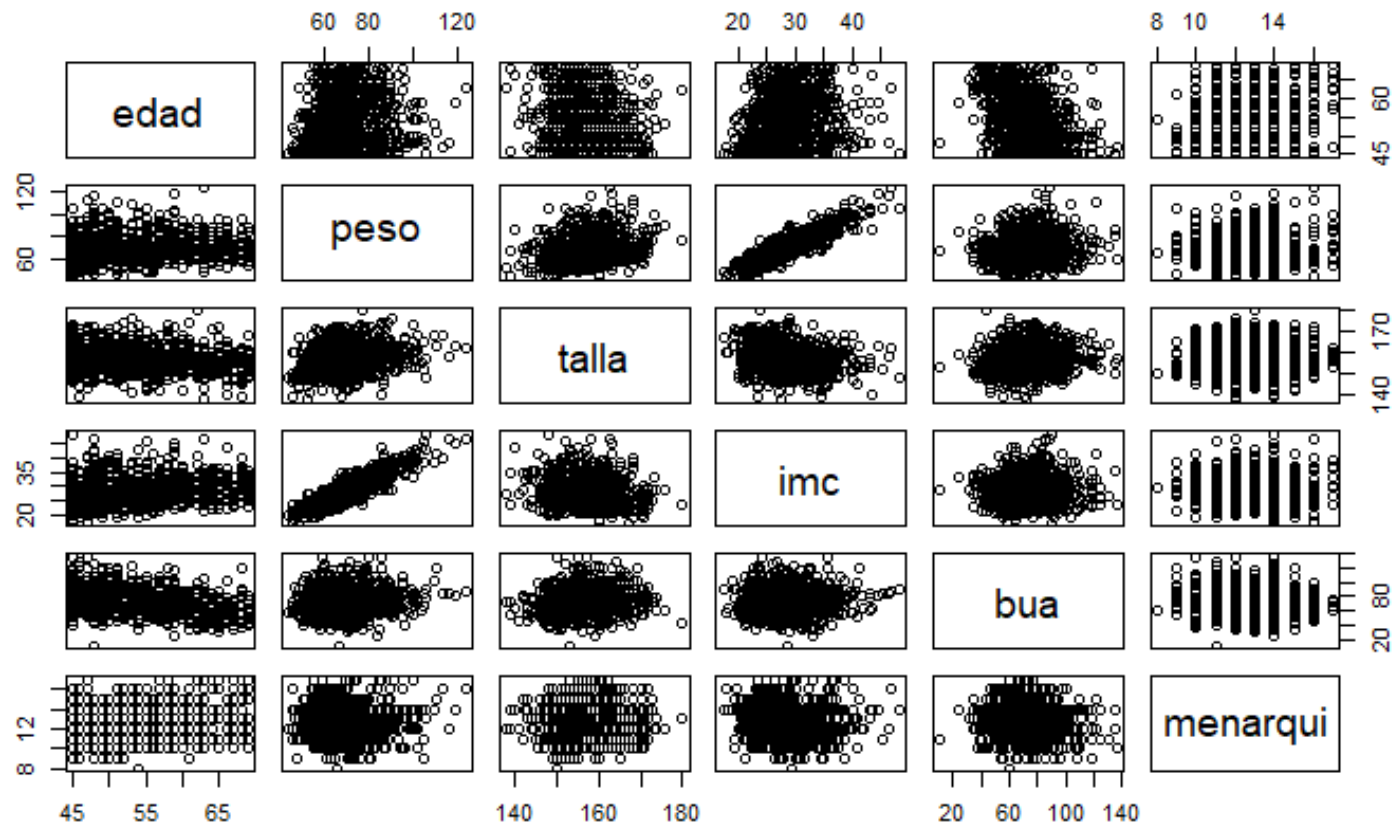
```
ggplot(osteoporosis, aes(x = edad, y = imc)) +  
  geom_point()
```



3. Bivariate analysis

3.3 Quantitative versus Quantitative

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



3. Bivariate analysis

3.3 Quantitative versus Quantitative

```
library(GGally)
```

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

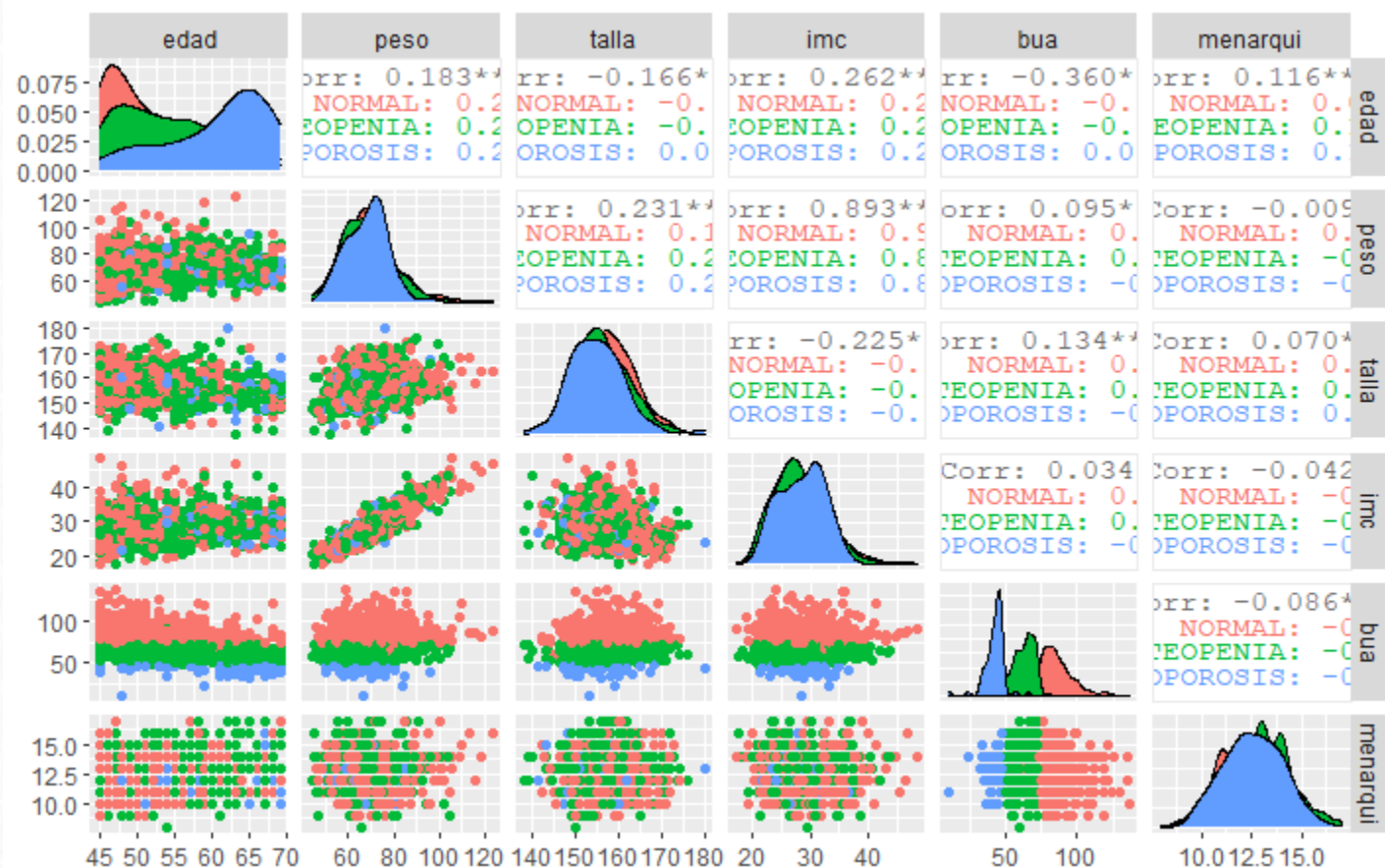


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4. Correlation

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2. Types of correlation (Pearson, Spearman)

4. Correlation

1. Definition

Main characteristics of correlation analysis:

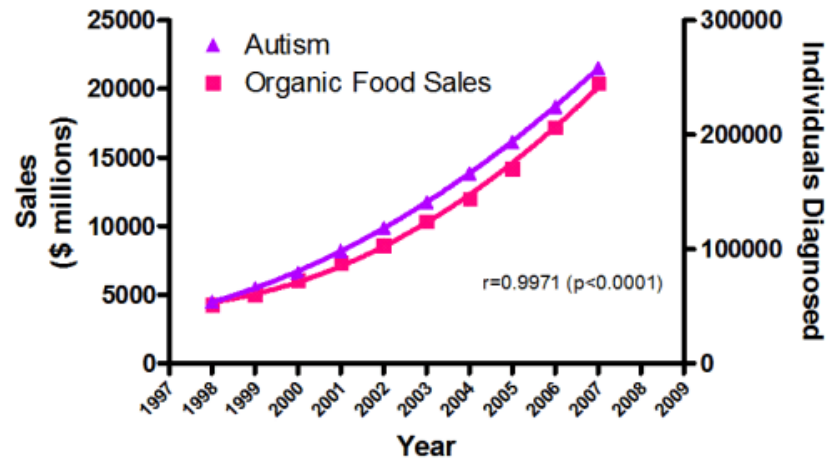
- Correlation analysis allow:
 - Study the **way** of relation between the two variables
 - **Quantify** the intensity of relation
- Correlation is **not causation** ➡ one thing does not causes the other
- In the correlation analysis, the two variables have the **same weigh**
- The **correlation coefficient** measures the strength of the relation

4. Correlation

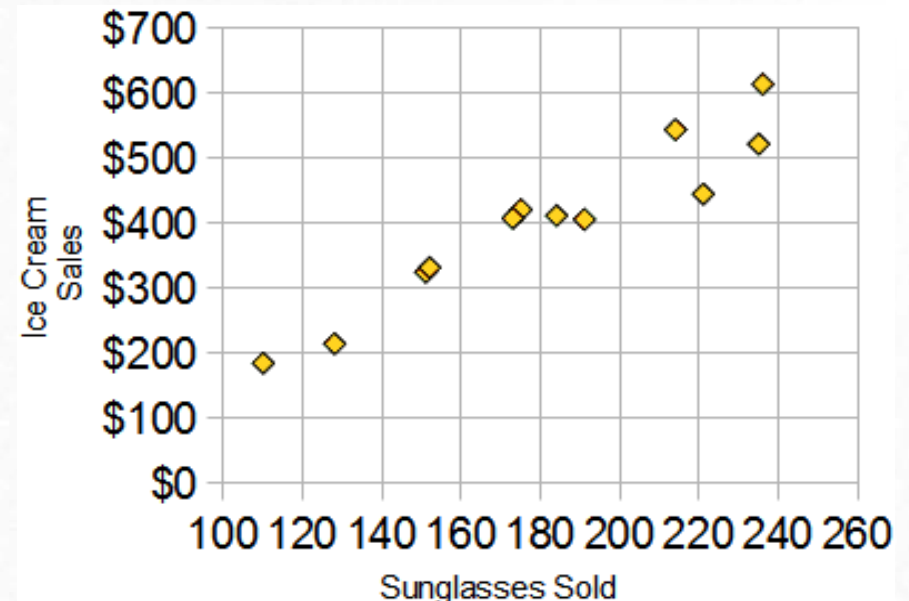
1. Definition

Main characteristics of correlation analysis:

Correlation is not causation



Sources: Organic Trade Association, 2011 Organic Industry Survey; U.S. Department of Education, Office of Special Education Programs, Data Analysis System (DANS), OMB# 1820-0043; *Children with Disabilities Receiving Special Education Under Part B of the Individuals with Disabilities Education Act



4. Correlation

2. Types of correlation

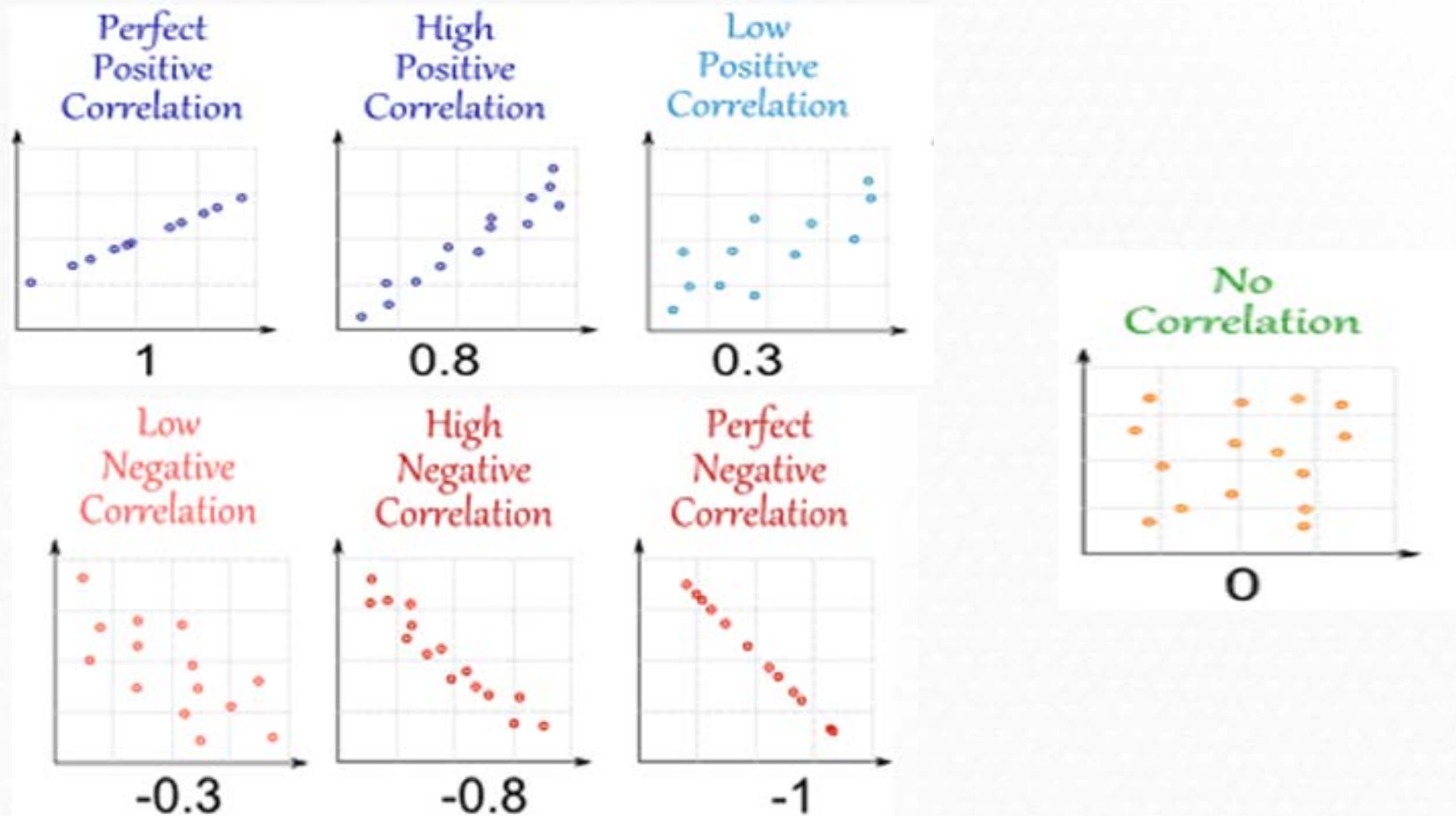
Pearson correlation coefficient

- 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

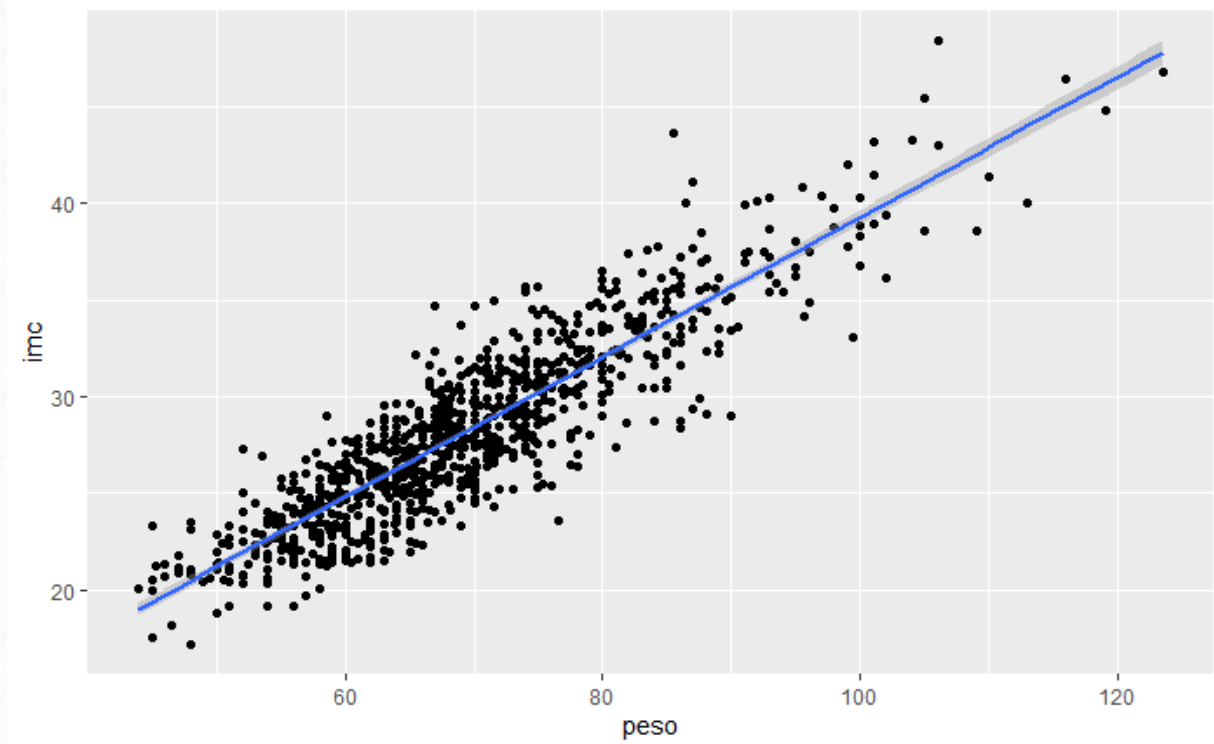
2. Types of correlation

Pearson correlation coefficient. How to in R?

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

```
cor(osteoporosis$peso, osteoporosis$imc, method = "pearson")
```

```
[1] 0.8927863
```



4. Correlation

2. Types of correlation

Pearson correlation coefficient. How to in R?

Bone density (bua) and **age (edad)** are correlated?

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
```

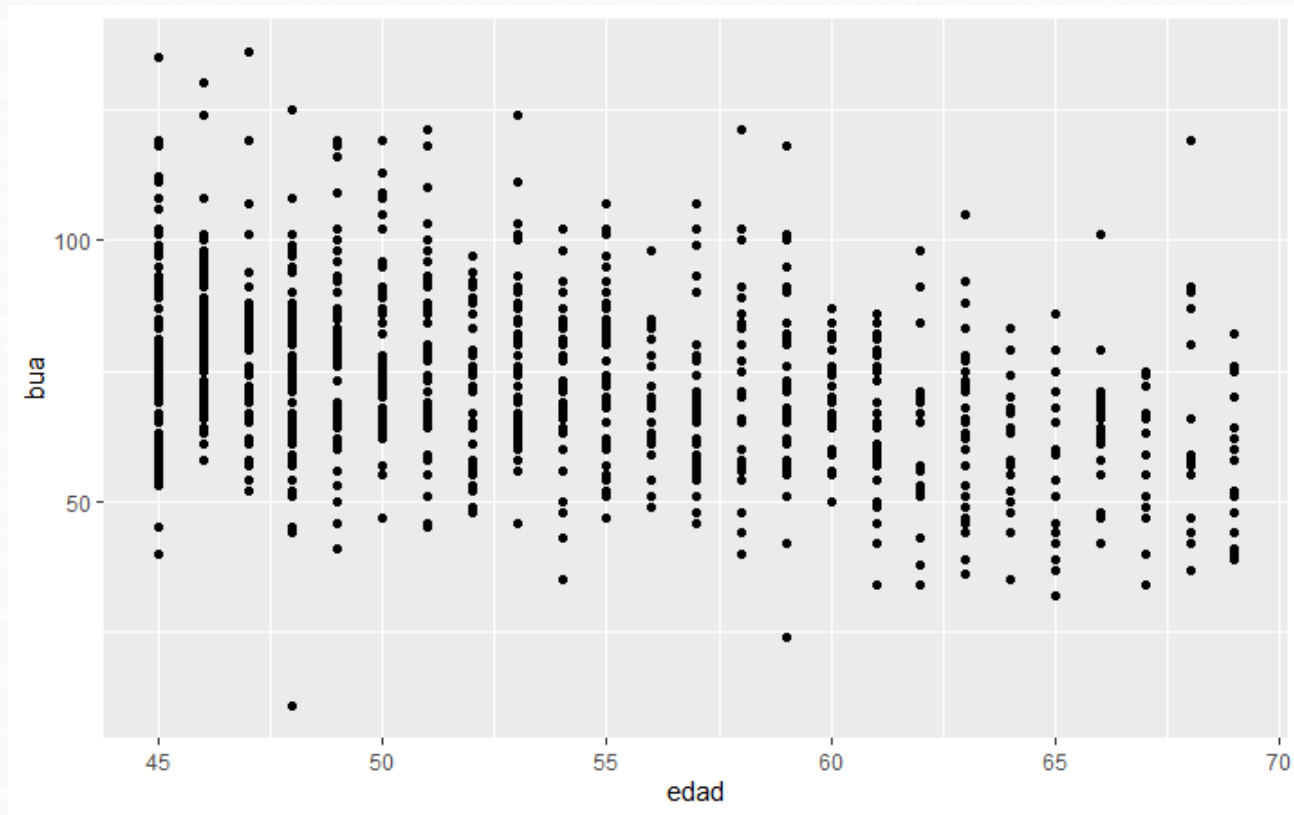
Don't forget to look the graphic!!

4. Correlation

2. Types of correlation

Pearson correlation coefficient. How to in R?

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



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 lineal



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).

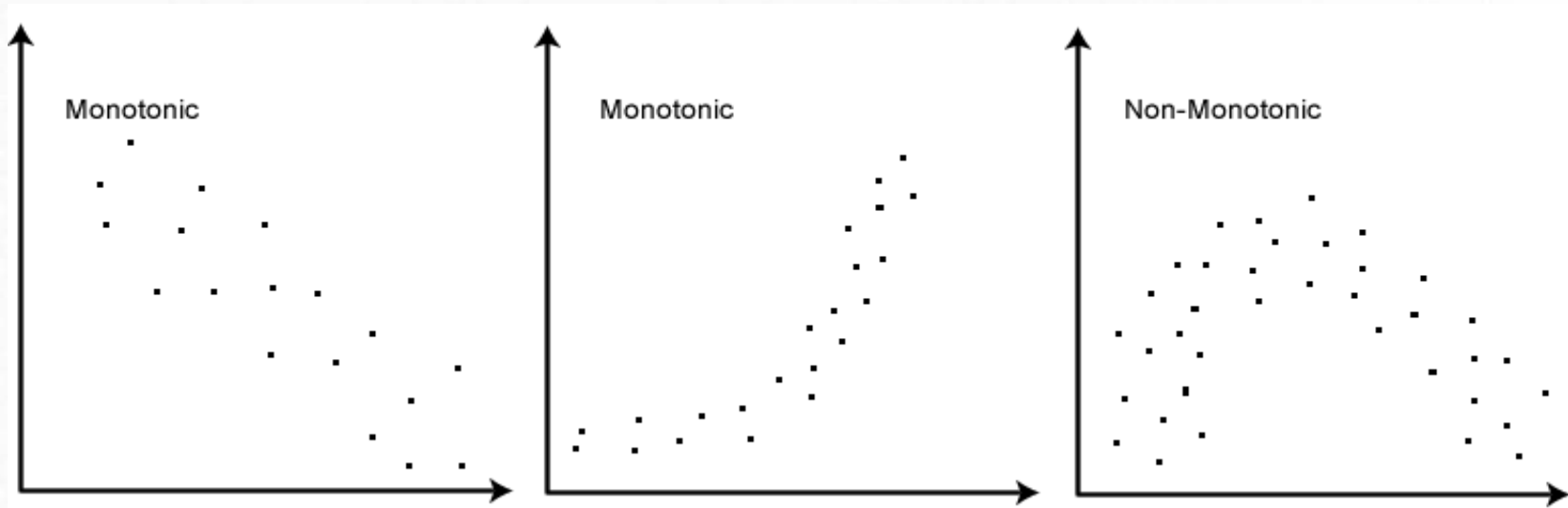


The variables tend to change together but not necessarily at a constant rate

4. Correlation

2. Types of correlation

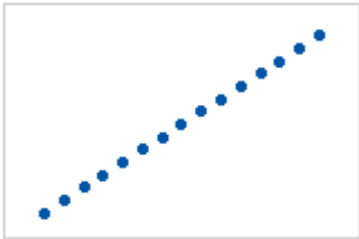
Non Parametric correlation: Spearman correlation coefficient



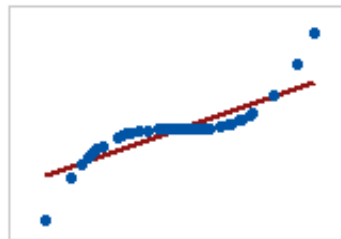
4. Correlation

2. Types of correlation

Comparison of Pearson and Spearman coefficients.



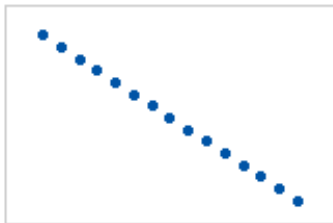
Pearson = +1, Spearman = +1



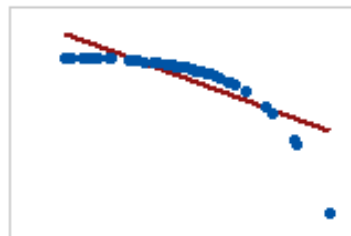
Pearson = +0.851, Spearman = +1



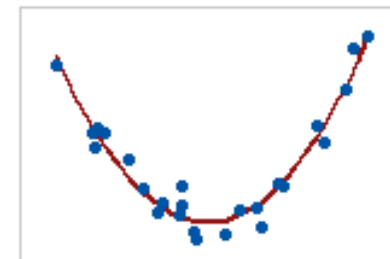
Pearson = -0.093, Spearman = -0.093



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