# R Programming & Descriptive statistics

Lecture 17

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CPES 2 - Fall 2022



## Today: Refresher on R Programming and Descriptive Statistics

#### 1. The basics of R programming

- 1.1. Types of R objects
- 1.2. The dplyr grammar
- 1.3. Data visualization

#### 2. Descriptive statistics

- 2.1. Distributions
- 2.2. Central tendency
- 2.3. Spread
- 2.4. Joint distributions

#### 3. A few words on using R

- 3.1. When it doesn't work the way you want
- 3.2. Where to find help
- 3.3. When it doesn't work at all



## Today: Refresher on R Programming and Descriptive Statistics

### 1. The basics of R programming

- 1.1. Types of R objects
- 1.2. The dplyr grammar
- 1.3. Data visualization



### 1.1. Types of R objects

• The most **basic** element in R is just a **value**, an object of dimension  $1 \times 1$ :

```
a <- 1
## [1] 1
b <- "monday"
## [1] "monday"
c <- a == b
## [1] FALSE
```



#### 1.1. Types of R objects

- Next, there are **vectors**, objects of dimension  $n \times 1$ :
  - Vectors can be created with **c()**
  - The elements of a vector should be of the **same class**
  - Class can be changed with **as** functions: as.[numeric/character/logical]()

Numeric	Character	Logical	Factor
a <- 1:4 a	b <- c("a", "xyz") b	c <- c(F, 1 < 2) c	d <- as.factor(a) d
## [1] 1 2 3 4	## [1] "a" "xyz"	## [1] FALSE TRUE	## [1] 1 2 3 4 ## Levels: 1 2 3 4
a * 2	paste0("b", b)	! c	relevel(d, 3)
## [1] 2 4 6 8	## [1] "ba" "bxyz"	## [1] TRUE FALSE	## [1] 1 2 3 4 ## Levels: 3 1 2 4



### 1.1. Types of R objects

• Some useful functions/operators for vectors

```
vec <- c("a", "b", "c", "d")
length(vec)
## [1] 4
match("b", vec)
## [1] 2
vec[3]
## [1] "c"
```



### 1.1. Types of R objects

- Finally, there are **tables**, objects of dimension  $n \times m$ :
  - $\circ$  Gather m vectors (columns) of n observations
  - Several possible classes, e.g., **tibble()** from tidyverse

data

```
## # A tibble: 3 x 3
## name age male
## <chr> <dbl> <lgl>
## 1 Bob 43 TRUE
## 2 Tom 19 TRUE
## 3 Kim 27 FALSE
```



#### 1.1. Types of R objects

- Such datasets can be imported on R with **read functions** 
  - There is one read function per **data format** (csv, xls, dta, ...)
  - The main argument is the **path**, with slashes: "C:/User/.../data.csv"

```
data <- read.csv("data/cereals.csv") # Import csv data</pre>
data <- as_tibble(data)</pre>
                              # Put in tibble format
                                   # Print first 5 rows
head(data, 5)
## # A tibble: 5 x 16
               mfr type calories protein fat sodium fiber carbo sugars potass
##
    name
    <chr>
          <chr> <chr> <int> <int> <int> <int> <dbl> <dbl> <int> <int>
## 1 100% Bran N
                                                    130
                                                                              280
                                 70
## 2 100% Natu~ 0
                                120
                                               5 15
                                                                             135
## 3 All-Bran
                                                                              320
                                70
                                                    260
## 4 All-Bran ~ K
                                                                              330
                                 50
                                                    140
## 5 Almond De~ R
                                110
                                                    200
                                                                 14
## # ... with 5 more variables: vitamins <dbl>, shelf <int>, weight <dbl>,
      cups <dbl>, rating <dbl>
## #
```



### 1.2. The dplyr grammar

• dplyr provides useful functions to manipulate data and the pipe operator (%>%) to chain operations

Important functions of the dplyr grammar

Function	Meaning
mutate()	Modify or create a variable
select()	Keep a subset of variables
filter()	Keep a subset of observations
arrange()	Sort the data
group_by()	Group the data
summarise()	Summarizes variables into 1 observation per group
left/right/inner/full_join()	Merge data



#### 1.2. The dplyr grammar

- We can first subset the data:
  - The type **variable** only takes the value "C", we can remove it with **select()**
  - Some **observations** have negative values of potassium, we can remove them with **filter()**
  - These two operations can be **chained** using the pipe operator %>%

```
dim(data) # Dimensions of the data before the operation

## [1] 77 16

data <- data %>%
    select(-type) %>%
    filter(potass >= 0)

dim(data) # Dimensions of the data after the operation

## [1] 75 15
```



### 1.2. The dplyr grammar

- The **mutate()** function allows to modify and create variables
  - Using simple vector operations
  - With **ifelse()** to create a binary variable based on a condition
  - With **case\_when()** to create a categorical variable



#### 1.2. The dplyr grammar

• Such computations can also be done **separately** for each value of a variable **with group\_by()** 

```
data <- data %>%
  group_by(mfr) %>%
  mutate(n_brands = n()) %>%
  ungroup()
```

- Using **summarise()** instead of mutate() allows to:
  - Keep only the grouping and summarized variables
  - Keep one value per group (no duplicate row)

```
data %>%
  group_by(mfr) %>%
  summarise(n_brands = n())
```



#### 1.2. The dplyr grammar

- dplyr also provides functions to:
  - Rename variables → rename()

```
data <- data %>% rename(manufacturer = mfr)
```

Sort rows according to the values of one or several variables → arrange()

```
data <- data %>% arrange(cal_100g)
```

○ Joining another dataset with a common variable → [left/right/full/inner]\_join():



#### 1.3. Data visualization

- The tidyverse packages also gives access to the **ggplot** grammar for data visualization
- The core arguments of the ggplot() function are the following
  - **Data**: the values to plot
  - **Mapping** (aes, for aesthetics): the structure of the plot
  - **Geometry**: the type of plot
- These arguments should be specified as follows:
  - Data and mapping should be specified within the parentheses
  - The geometry and any other element should be added with a + sign

```
ggplot(data, aes) + geometry + anything_else
```

• You can also apply the ggplot() function to your data with a pipe:

```
data %>% ggplot(., aes) + geometry
```

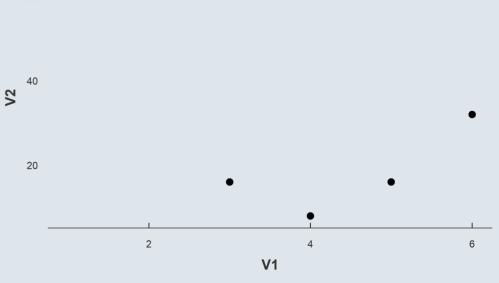


#### 1.3. Data visualization

• We first specified our data:

V1 1 2 3 4 5 6 V2 64 60 16 8 16 32

- Then assigned V1 to the x-axis and V2 to the y-axis with aes()
- And chose the point geometry with a size of 3





#### 1.3. Data visualization

- In some cases you would convey information with other means than a position on axis
  - It can be with the color, size or shape of a geometry, ...
  - For instance if you have two groups

```
test_data <- test_data %>% mutate(Group = paste("Group", c(1, 1, 2, 2, 2, 2)))
```

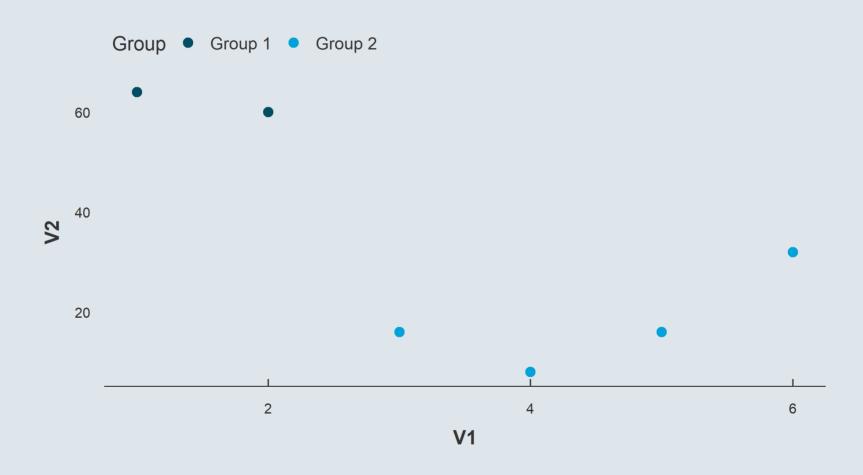
<b>V1</b>	V2	Group
1	64	Group 1
2	60	Group 1
3	16	Group 2
4	8	Group 2
5	16	Group 2
6	32	Group 2

• Just as we assigned the two numeric variables to the x an y axis with aes, we have to assign the group variable to the 'color axis' with aes

• But there is no proper 'color axis', that's why a legend will be generated



### 1.3. Data visualization





#### 1.3. Data visualization

- → Case 1: The style does not depend on the value of a variable
  - The style element should be **uniform** across all data points
    - So it should be specified **within the geometry** function

```
ggplot(test_data, aes(x = V1, y = V2)) +
  geom_point(color = "red", shape = 18)
```

- → Case 2: The style element depends on the value of a variable
  - The style should **depend on the value of the variable** it has been assign to in **aes** 
    - o So just as for regular axes, modifications should take place in a scale function

```
ggplot(test_data, aes(x = V1, y = V2, color = Group)) +
   scale_color_manual(name = "Group:", values = c("red", "blue")) +
   geom_point(shape = 18)
```

### Practice

1) Import the dataset cereals.csv

2) There is no documentation on the variable rating. Use the summary() function to deduce the unit of the variable based on its distribution.

3) Generate a scatter plot with sugars on the x axis and rating on the y axis to deduce whether the rating was made by nutritionists or consumers

You've got 10 minutes!

### Solution

1) Import the dataset cereals.csv

```
cereals <- read.csv("C:/User/Documents/cereals.csv")</pre>
```

2) There is no documentation on the variable rating. Use the summary() function to deduce the unit of the variable based on its distribution.

```
summary(cereals$rating)
```

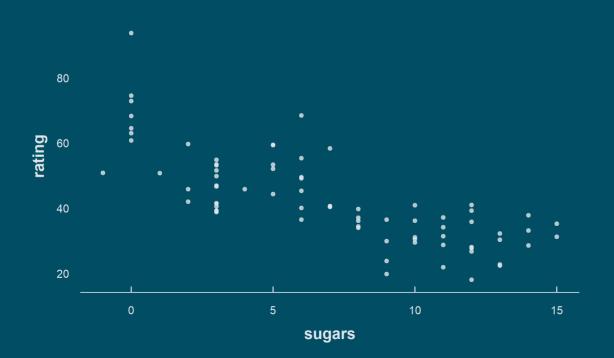
```
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 18.04 33.17 40.40 42.67 50.83 93.70
```

The variable is probably in percentages

### Solution

3) Generate a scatter plot with <mark>sugars</mark> on the x axis and rating on the y axis to deduce whether the rating was made by nutritionists or consumers

```
ggplot(cereals, aes(x = sugars, y = rating)) +
  geom_point(alpha = .8)
```



The rating was probably made by nutritionists

### Overview



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#### 2. Descriptive statistics

- 2.1. Distributions
- 2.2. Central tendency
- 2.3. Spread
- 2.4. Joint distributions

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#### 2.1. Distributions

- The point of **descriptive statistics** is to **summarize variables** into a small set of tractable statistics.
- The most comprehensive way to characterize a variable is to compute its distribution:
  - What are the values the variable takes?
  - How frequently does each of these values appear?

#### → Consider for instance the following variable:

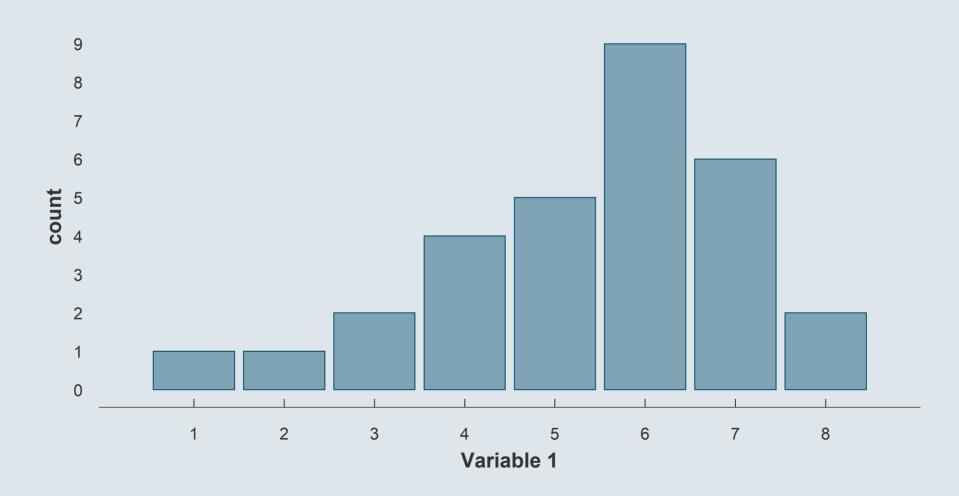
	Variable 1																												
3	5	4	6	5	4	5	7	7	6	1	7	6	7	6	4	7	7	6	6	5	6	6	3	4	5	2	6	8	8

We can count how many times each value appears

Variable 1	1	2	3	4	5	6	7	8
n	1	1	2	4	5	9	6	2

- And we can represent this distribution graphically with a bar plot
  - Each possible value on the x-axis
  - Their number of occurrences on the y-axis







#### 2.1. Distributions

• But what if we would like to do the same thing for the following variable?

Variable 2										
5.912877	5.006781	5.517149	5.854849	5.177872	3.815240					
1.666582	4.422721	6.025062	5.411020	5.889811	6.729103					
4.160800	6.519049	6.849172	8.368158	6.167404	2.882974					
6.751888	3.202183	6.390224	3.942039	6.488909	8.195647					
7.073922	4.790039	5.297919	1.218109	5.754213	7.225030					

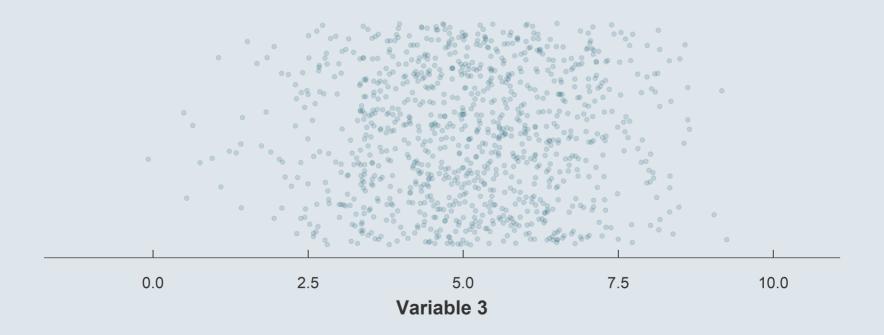
- Each value appears only once
  - So the count of each value does not help summarizing the variable

→We should rather do a histogram



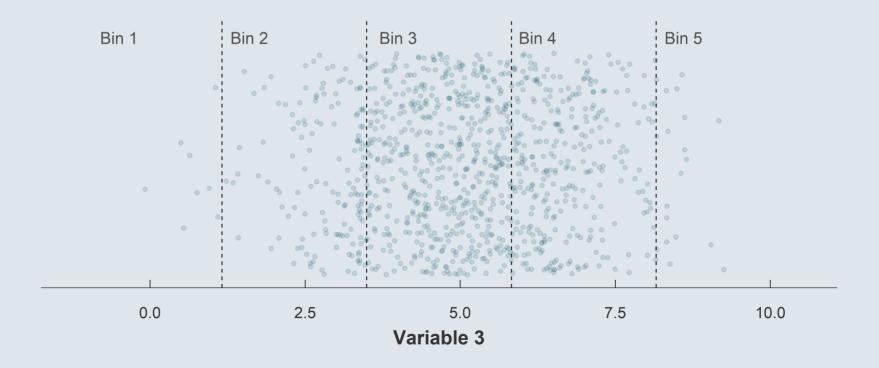
#### 2.1. Distributions

• Consider for instance the following variable. For clarity each point is shifted vertically by a random amount.



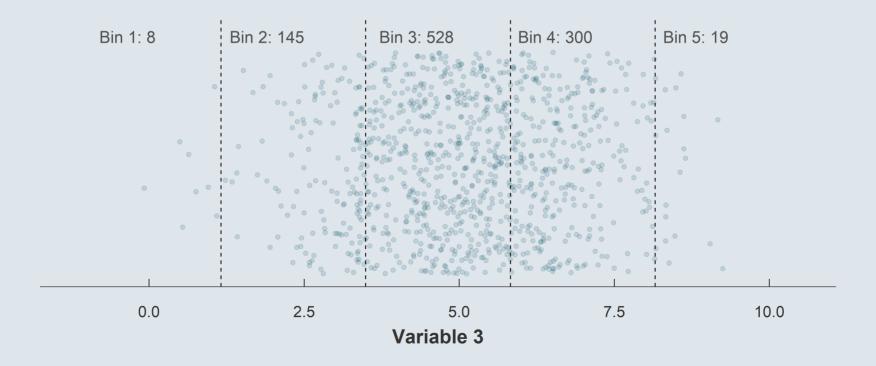


- Consider for instance the following variable. For clarity each point is shifted vertically by a random amount.
  - We can divide the domain of this variable into 5 bins



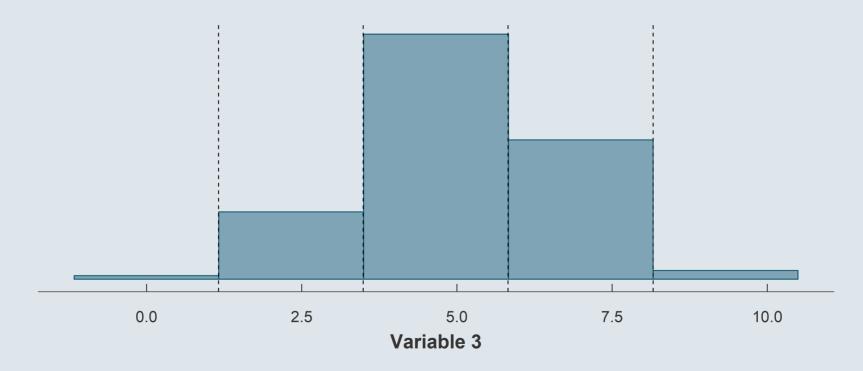


- Consider for instance the following variable. For clarity each point is shifted vertically by a random amount.
  - We can divide the domain of this variable into 5 bins
  - And count the number of observations within each bin



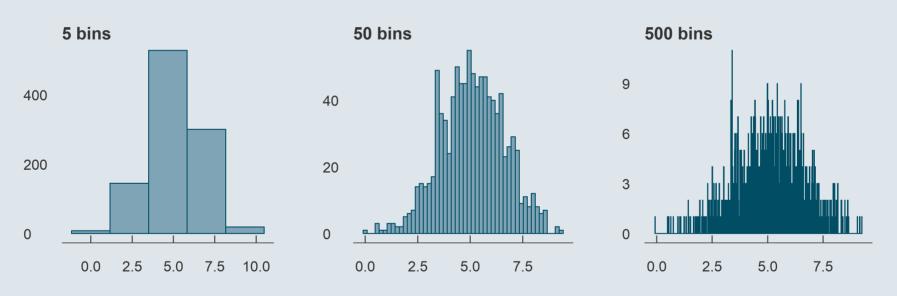


- Consider for instance the following variable. For clarity each point is shifted vertically by a random amount.
  - We can divide the domain of this variable into 5 bins
  - And count the number of observations within each bin





- There's no definitive rule to choose the number of bins
  - But too many or too few can yield misleading histograms



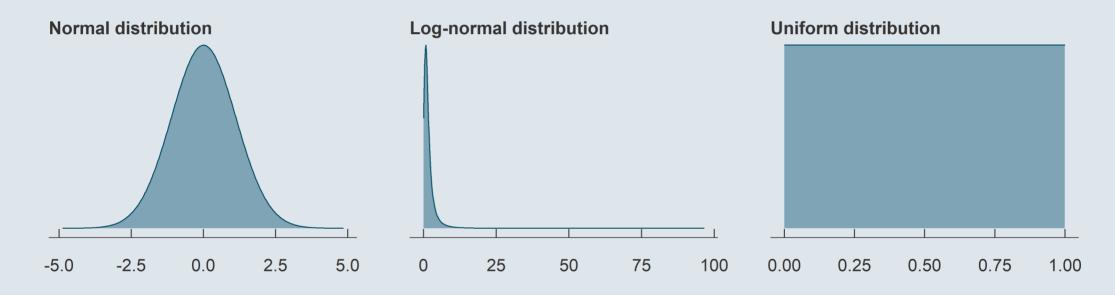
- Densities are often used instead of histograms
  - Both are based on the same principle, but densities are continuous

# Ħ

## 2. Descriptive statistics

#### 2.1. Distributions

• Distributions are comprehensive representations but not simple statistics

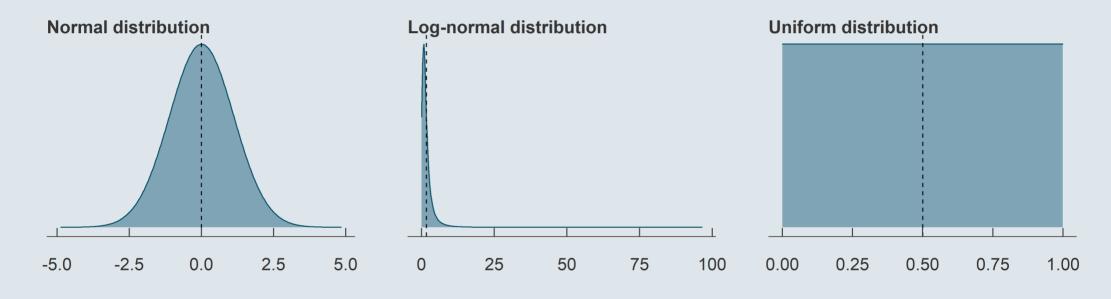


• How to summarize these distributions with simple statistics?



#### 2.1. Distributions

• Distributions are comprehensive representations but not simple statistics



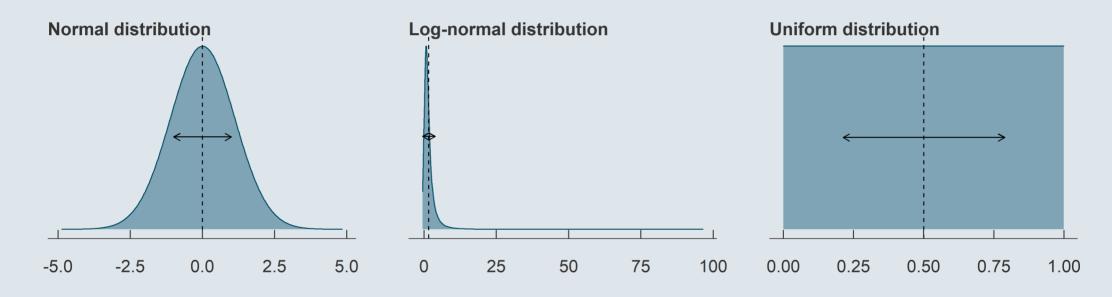
- How to summarize these distributions with simple statistics?
  - By describing their central tendency (e.g., mean, median)

# #

## 2. Descriptive statistics

#### 2.1. Distributions

Distributions are comprehensive representations but not simple statistics



- How to summarize these distributions with simple statistics?
  - By describing their central tendency (e.g., mean, median)
  - And their spread (e.g., standard deviation, inter-quartile range)



#### 2.2. Central tendency

- The mean is the most common statistic to describe central tendencies
  - Take for instance the grades of group 2 last year for the second-semester final project

Grades of G2 last year										
20	17.5	16	16.0	14.5	19.5	18.5				
20	17.5	16	14.5	19.5	18.5	18.5				

• The mean is simply the sum of all the grades divided by the number of grades:

$$ar{x} = rac{1}{N} \sum_{i=1}^N x_i$$

$$\frac{20 + 20 + 17.5 + 17.5 + 16 + 16 + 16 + 16 + 14.5 + 14.5 + 19.5 + 19.5 + 18.5 + 18.5 + 18.5}{14} = 17.61$$



### 2.2. Central tendency

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  - Take for instance the grades of group 2 last year for the second-semester final project

Grades of G2 last year										
20	17.5	16	16.0	14.5	19.5	18.5				
20	17.5	16	14.5	19.5	18.5	18.5				

• It can also be expressed as the average of each possible value weighted by its number of occurrences:

$$ar{x} = rac{1}{N} \sum_{i=1}^N x_i$$

$$\bar{x} = \frac{(2 \times 20) + (2 \times 17.5) + (3 \times 16) + (2 \times 14.5) + (2 \times 19.5) + (3 \times 18.5)}{2 + 2 + 3 + 2 + 2 + 3 = 14} = 17.61$$



### 2.2. Central tendency

• To obtain the median you first need to sort the values:

Grades of G2 last year													
1	2	3	4	5	6	7	8	9	10	11	12	13	14
14.5	14.5	16	16	16	17.5	17.5	18.5	18.5	18.5	19.5	19.5	20	20

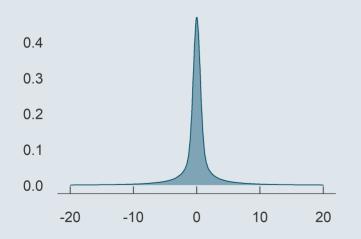
- The median is the value that divides the distribution into two halves
  - With N even: Average of the last value of the first half and the first value of the second half
- As we have 14 observations, here the median is the average of the 7<sup>th</sup> and the 8<sup>th</sup> observations:

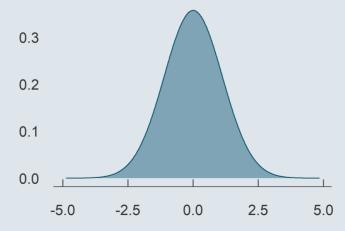
$$\operatorname{Med}(x) = \left\{ egin{array}{ll} x[rac{N+1}{2}] & ext{if $N$ is odd} \ rac{x[rac{N}{2}] + x[rac{N}{2} + 1]}{2} & ext{if $N$ is even} \end{array} 
ight. = rac{17.5 + 18.5}{2} = 18$$



### 2.3. Spread

- The most intuitive statistic to describe the spread of a variable is probably its **range** 
  - The minimum and maximum value of the distribution
- But consider the following two distributions:





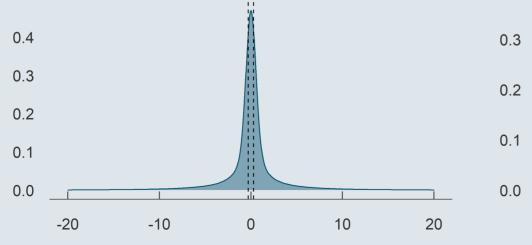
- In the presence of outliers or very skewed distributions, the full range of a variable may not be representative of what we mean by 'spread'
- That's why we tend to prefer:
  - The inter-quantile range
  - The **standard deviation**

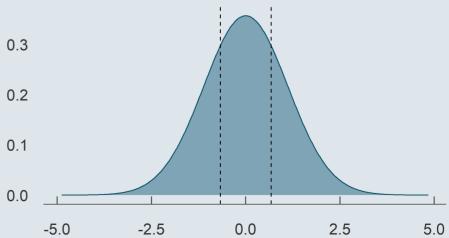
# #

### 2. Descriptive statistics

### 2.3. Spread

- Quantiles are observations that divide the population into groups of equal size
  - The median divides the population into 2 groups of equal size
  - o Quartiles divide the population into 4 groups of equal size
  - There are also terciles, quintiles, deciles, and so on
- ullet The interquartile range is the difference between the third and the first quartile:  ${
  m IQR}=Q_3-Q_1$ 
  - Put differently, it corresponds to the bounds of the set which contains the **middle half of the distribution**







### 2.3. Spread

- The **variance** is a way to quantify how values of a variable tend to deviate from their mean
  - If values tend to be close to the mean, then the spread is low
  - If values tend to be far from the mean, then the spread is large
- Because deviations from the mean sum to 0, they have to be squared
  - This is how the variance is computed: by **averaging the squared deviations from the mean**

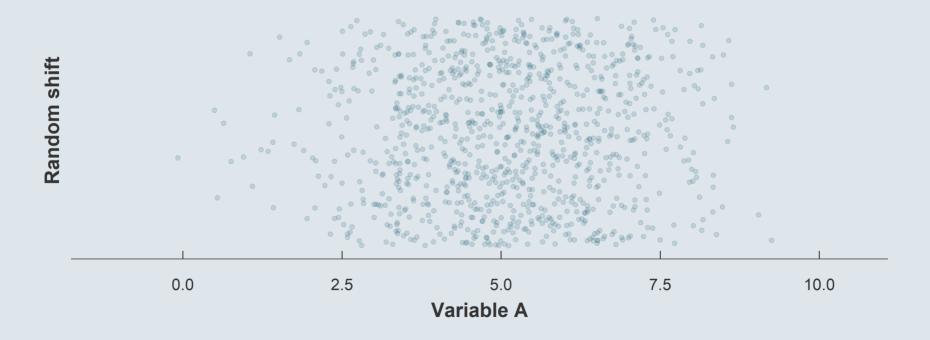
$$ext{Var}(x) = rac{1}{N} \sum_{i=1}^N (x_i - ar{x})^2$$

- The variance is a sum of squares, so we have to take its square root to remain in the same unit as the data
  - This is what we call the **standard deviation**

$$\mathrm{SD}(x) = \sqrt{\mathrm{Var}(x)} = \sqrt{rac{1}{N} \sum_{i=1}^N (x_i - ar{x})^2}$$

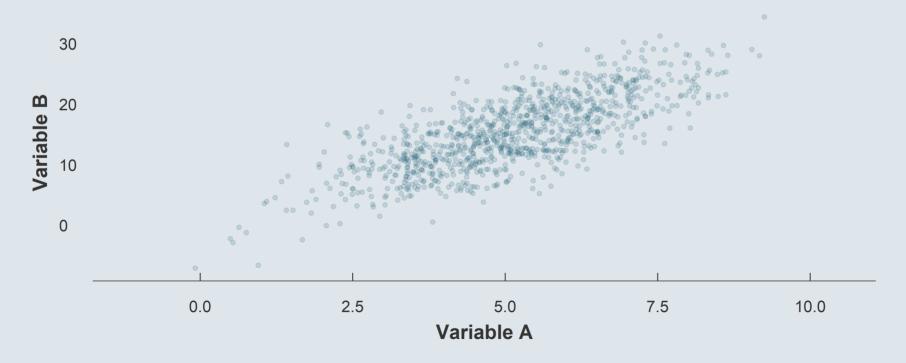


- The joint distribution shows the possible values and associated frequencies for two variables simultaneously
  - Earlier we plotted the observations of a variable on a line, randomly shifted on the vertical axis





- The joint distribution shows the possible values and associated frequencies for two variable simultaneously
  - Earlier we plotted the observations of a variable on a line, randomly shifted on the vertical axis
  - o Instead of shifting observations randomly, vertical coordinates can indicate the value of a second variable





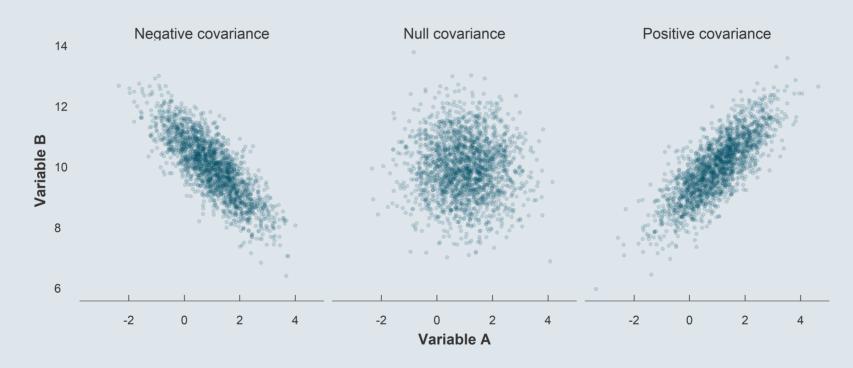
- When describing a single distribution, we're interested in its spread and central tendency
- When describing a joint distribution, we're interested in the relationship between the two variables
  - This can be characterized by the covariance

$$\mathrm{Cov}(x,y) = rac{1}{N} \sum_{i=1}^N (x_i - ar{x})(y_i - ar{y})$$

- The contribution of observation i to Cov(x, y) is:
  - $\circ$  Positive when both  $x_i$  and  $y_i$  are above their respective mean
  - $\circ$  Positive when both  $x_i$  and  $y_i$  are below their respective mean
  - $\circ$  Negative when  $x_i$  and  $y_i$  are on different sides of their respective mean
  - → If y tends to be large relative to its mean when x is large relative to its mean, their covariance is positive.

    Conversely, if one tends to be large when the other tends to be low, the covariance is negative.





- One disadvantage of the **covariance** is that is it **not standardized** 
  - You cannot directly compare the covariance of two pairs of completely different variables
  - $\circ$  Theoretically the covariance can take values from  $-\infty$  to  $+\infty$

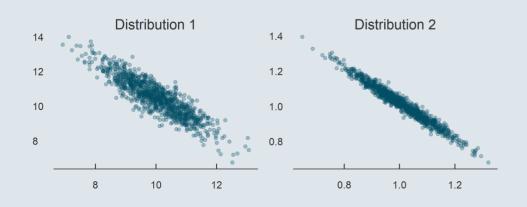


### 2.4. Joint distributions

- This is why we often use the **correlation coefficient** 
  - It is obtained by dividing the covariance by the product of the standard deviation of the two variables
  - This allows to **standardize the coefficient** between -1 and 1

$$\mathrm{Corr}(x,y) = rac{\mathrm{Cov}(x,y)}{\mathrm{SD}(x) imes \mathrm{SD}(y)}$$

• Consider for instance the following two distributions:



- Here the association between the two variables feels tighter on the right panel
  - But the covariance is larger for the first relationship because units are larger
  - While the correlation, standardized between
     0 and 1, is larger for the second one

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#### 3.1. When it doesn't work the way you want

- When things do not work the way you want, **NA**s are the usual suspects
  - For instance, this is how the mean function reacts to NAs:

```
mean(c(1, 2, NA)) 

## [1] NA 

## [1] 1.5
```

- Here it is obvious that NAs are the problem, but when chaining operations it's not always that transparent
   So check your data using is.na() to see whether NAs could mess things up
- is.na(c(1, 2, NA))
  ## [1] FALSE FALSE TRUE



#### 3.2. Where to find help

- You can find help on help files
  - Sometimes things don't work just because you did not understand the arguments of the function
  - Just enter the name of the function preceded by a ? in your console
  - The help file will appear in the Help tab of R studio

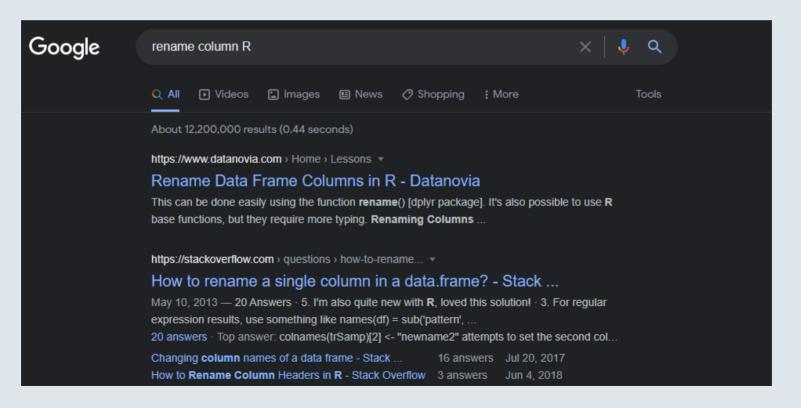
#### ?pivot\_longer

Arguments	
data	A data frame to pivot.
cols	< <u>tidy-select</u> > Columns to pivot into longer format.
names_to	A string specifying the name of the column to create from the data stored in the column names of data.
	Can be a character vector, creating multiple columns, if names_sep or names_pattern is provided. In this case, there are two special values you can take advantage of:
	NA will discard that component of the name.
	<ul> <li>.value indicates that component of the name defines the name of the column containing the cell values, overriding values_to.</li> </ul>
names_prefix	A regular expression used to remove matching text from the start of each variable name.



#### 3.2. Where to find help

- When it doesn't work, search on the **internet** 
  - **Every question** you might have at that stage is already asked and **answered** at stackoverflow.com





#### 3.3. When it doesn't work at all

• Sometimes R breaks and returns an error, which is usually kind of cryptic

```
read.csv("C:\Users\l.sirugue\Documents\R")
```

## Error: '\U' non suivi de chiffres hexadécimaux dans la chaîne de caractères débutant ""C:\U"

- Try to look for keywords that might help you understand where it comes from
- And paste it in Google with the name of your command, chances are many people already struggled with that

