

Univariate regressions

Lecture 8

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CPES 2 - Fall 2022



Part I recap

Import data

```
fb <- read.csv("C:/User/Documents/ligue1.csv", encoding = "UTF-8")
```

Class

```
is.numeric("1.6180339") # What would be the output?
```

```
## [1] FALSE
```

Subsetting

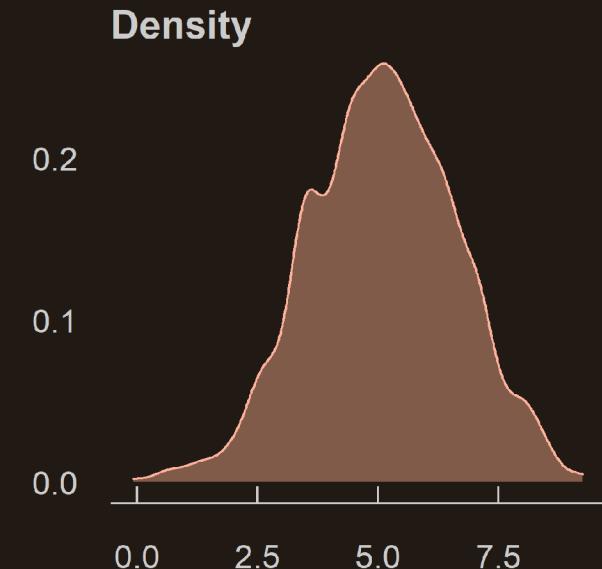
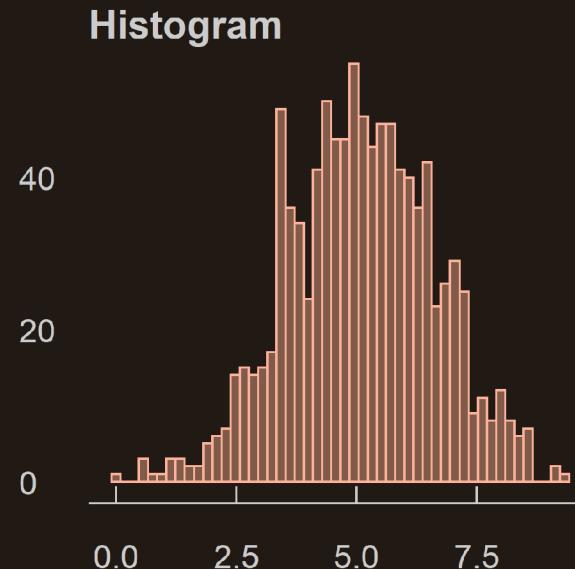
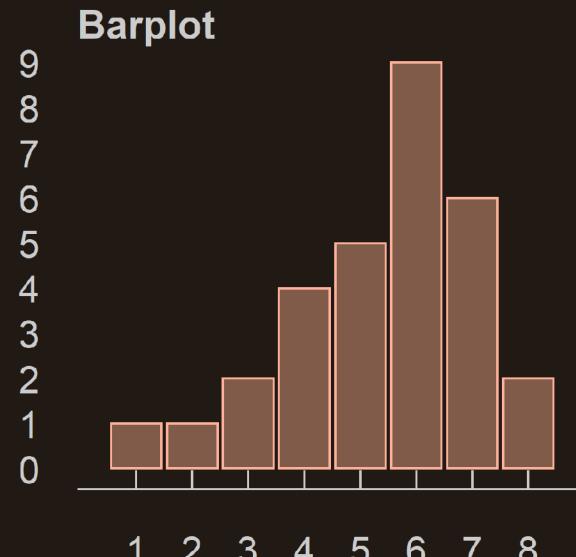
```
fb$Home[3]
```

```
## [1] "Troyes"
```

Part I recap

Distributions

- The **distribution** of a variable documents all its possible values and how frequent they are

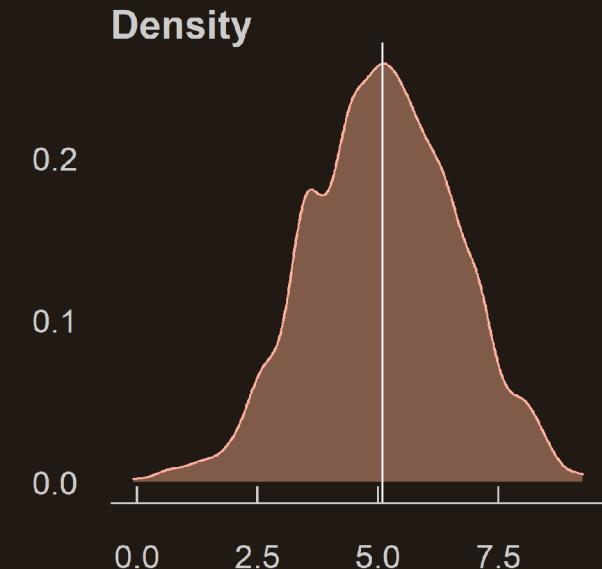
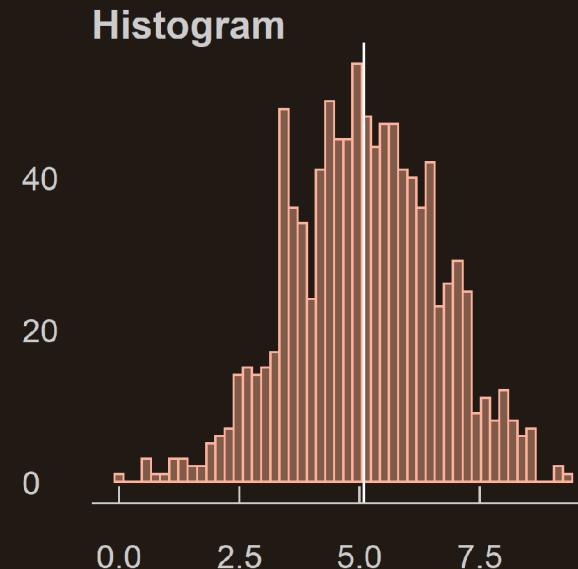
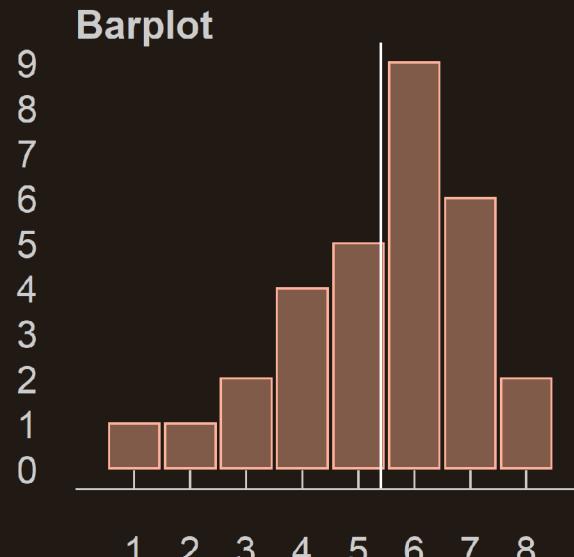


- We can describe a distribution with:

Part I recap

Distributions

- The **distribution** of a variable documents all its possible values and how frequent they are

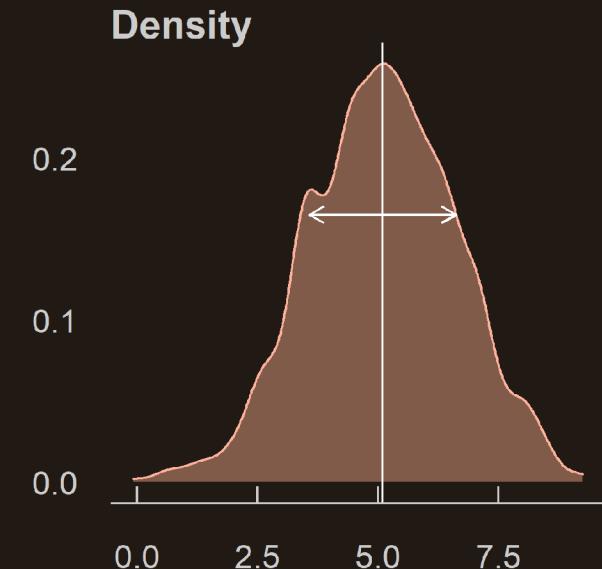
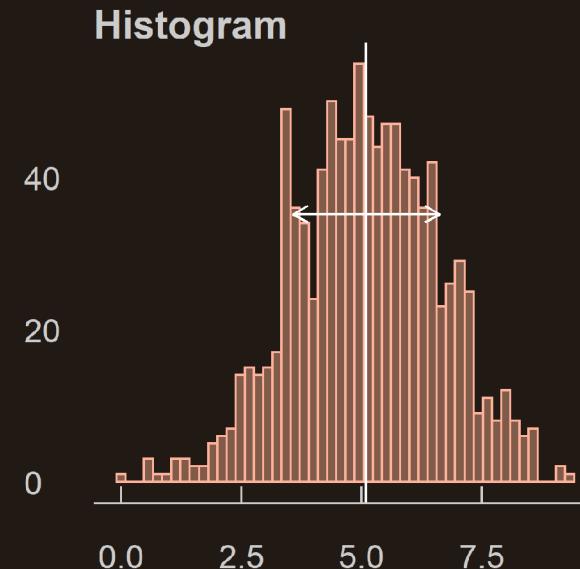
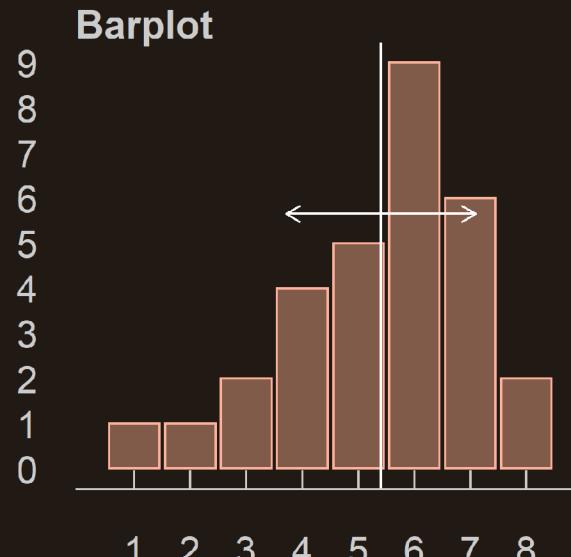


- We can describe a distribution with:
 - Its **central tendency**

Part I recap

Distributions

- The **distribution** of a variable documents all its possible values and how frequent they are



- We can describe a distribution with:
 - Its **central tendency**
 - And its **spread**



Part I recap

Central tendency

- The **mean** is the sum of all values divided by the number of observations

$$\bar{x} = \frac{1}{N} \sum_{i=1}^N x_i$$

- The **median** is the value that divides the (sorted) distribution into two groups of equal size

$$\text{Med}(x) = \begin{cases} x\left[\frac{N+1}{2}\right] & \text{if } N \text{ is odd} \\ \frac{x\left[\frac{N}{2}\right] + x\left[\frac{N}{2} + 1\right]}{2} & \text{if } N \text{ is even} \end{cases}$$

Spread

- The **standard deviation** is square root of the average squared deviation from the mean

$$\text{SD}(x) = \sqrt{\text{Var}(x)} = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^2}$$

- The **interquartile range** is the difference between the maximum and the minimum value from the middle half of the distribution

$$\text{IQR} = Q_3 - Q_1$$

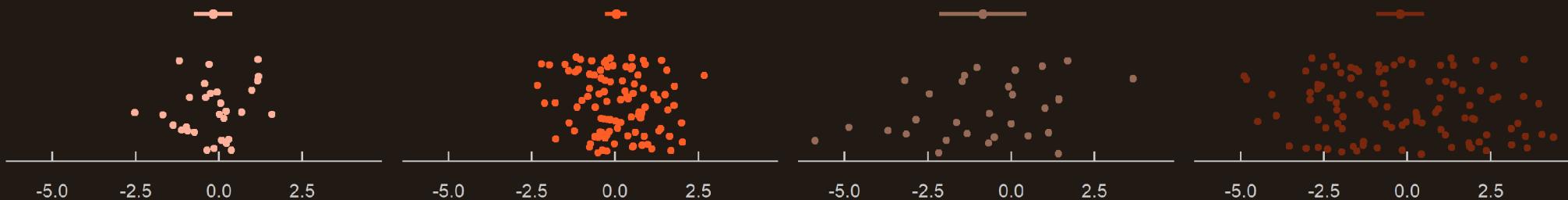
Part I recap

Inference

- In Statistics, we view variables as a given realization of a **data generating process**
 - Hence, the **mean** is what we call an **empirical moment**, which is an **estimation...**
 - ... of the **expected value**, the **theoretical moment** of the DGP we're interested in
- To know how confident we can be in this estimation, we need to compute a **confidence interval**

$$[\bar{x} - t_{n-1, 97.5\%} \times \frac{\text{SD}(x)}{\sqrt{n}}; \bar{x} + t_{n-1, 97.5\%} \times \frac{\text{SD}(x)}{\sqrt{n}}]$$

- It gets **larger** as the **variance** of the distribution of x increases
- And gets **smaller** as the **sample size** n increases



Part I recap

Packages

```
library(dplyr)
```

Main dplyr functions

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



Part I recap

Merge data

```
a <- data.frame(x = c(1, 2, 3), y = c("a", "b", "c"))
b <- data.frame(x = c(4, 5, 6), y = c("d", "e", "f"))
c <- data.frame(x = 1:6, z = c("alpha", "bravo", "charlie", "delta", "echo", "foxtrot"))
```

```
a %>% bind_rows(b) %>% left_join(c, by = "x")
```

x	y	z
1	a	alpha
2	b	bravo
3	c	charlie
4	d	delta
5	e	echo
6	f	foxtrot



Part I recap

Reshape data

country	year	share_tertiary	share_gdp
FRA	2015	44.69	3.40
USA	2015	46.52	3.21

```
data %>% pivot_longer(c(share_tertiary, share_gdp), names_to = "Variable", values_to = "Value")
```

country	year	Variable	Value
FRA	2015	share_tertiary	44.69
FRA	2015	share_gdp	3.40
USA	2015	share_tertiary	46.52
USA	2015	share_gdp	3.21



Part I recap

The 3 core components of the ggplot() function

Component	Contribution	Implementation
Data	Underlying values	ggplot(data, data %>% ggplot(.,
Mapping	Axis assignment	aes(x = V1, y = V2, ...))
Geometry	Type of plot	+ geom_point() + geom_line() + ...

- Any **other element** should be added with a **+ sign**

```
ggplot(data, aes(x = V1, y = V2)) +  
  geom_point() + geom_line() +  
  anything_else()
```



Part I recap

Main customization tools

Item to customize	Main functions
Axes	scale_[x/y]_[continuous/discrete]
Baseline theme	theme_[void/minimal/.../dark]()
Annotations	geom_--[[h/v]line/text](), annotate()
Theme	theme(axis.[line/ticks].[x/y] = ...,

Main types of geometry

Geometry	Function
Bar plot	geom_bar()
Histogram	geom_histogram()
Area	geom_area()
Line	geom_line()
Density	geom_density()
Boxplot	geom_boxplot()
Violin	geom_violin()
Scatter plot	geom_point()



Part I recap

Main types of aesthetics

Argument	Meaning
alpha	opacity from 0 to 1
color	color of the geometry
fill	fill color of the geometry
size	size of the geometry
shape	shape for geometries like points
linetype	solid, dashed, dotted, etc.

- If specified **in the geometry**
 - It will apply uniformly to every **all the geometry**
- If assigned to a variable **in aes**
 - it will **vary with the variable** according to a scale documented in legend

```
ggplot(data, aes(x = V1, y = V2, size = V3)) +  
  geom_point(color = "steelblue", alpha = .6)
```



Part I recap

R Markdown: Three types of content

```
1 ---  
2 title: "Report example"  
3 author: "Louis Sirugue"  
4 date: "26/09/2021"  
5 output: html_document  
6 ---  
7  
8 ## overview of the data  
9  
10 ```{r cars}  
11 # Omit if distance >= 100  
12 cars <- cars[cars$dist < 100, ]  
13 names(cars)  
14 dim(cars)  
15 c(mean(cars$speed), mean(cars$dist))  
16  
17  
18 The dataset we consider contains two variables, speed and distance, and has `r  
dim(cars)[1]` observations. The average speed value is `r mean(cars$speed)` and  
the average distance value is `r mean(cars$dist)`.
```

Report example

Louis Sirugue

26/09/2021

Overview of the data

```
# Omit if distance >= 100  
cars <- cars[cars$dist < 100, ]  
names(cars)
```

```
## [1] "speed" "dist"
```

```
dim(cars)
```

```
## [1] 49  2
```

```
c(mean(cars$speed), mean(cars$dist))
```

```
## [1] 15.22449 41.40816
```

The dataset we consider contains two variables, speed and distance, and has 49 observations. The average speed value is 15.2244898 and the average distance value is 41.4081633.

YAML header

Code chunks

Text



Part I recap

Useful features

→ **Inline code** allows to include the output of some **R code within text areas** of your report

Syntax

```
`paste("a", "b", sep = "-")`
```

```
`r paste("a", "b", sep = "-")`
```

Output

```
paste("a", "b", sep = "-")
```

a-b

→ **kable()** for clean **html tables** and **datatable()** to navigate in **large tables**

```
kable(results_table)  
datatable(results_table)
```



Part I recap

LaTeX for equations

- *LATEX* is a convenient way to display **mathematical** symbols and to structure **equations**
 - The **syntax** is mainly based on **backslashes ** and **braces {}**

→ What you **type** in the text area: `$x \neq \frac{\alpha \times \beta}{2}$`

→ What is **rendered** when knitting the document: $x \neq \frac{\alpha \times \beta}{2}$

To **include** a **LaTeX equation** in R Markdown, you simply have to surround it with the **\$ sign**

The mean formula with one \$ on each side

→ For inline equations

$$\bar{x} = \frac{1}{N} \sum_{i=1}^N x_i$$

The mean formula with two \$ on each side

→ For large/emphasized equations

$$\bar{x} = \frac{1}{N} \sum_{i=1}^N x_i$$



Today: *We start Econometrics!*

1. Joint distributions

- 1.1. Definition
- 1.2. Covariance
- 1.3. Correlation

2. Univariate regressions

- 2.1. Introduction to regressions
- 2.2. Coefficients estimation

3. Binary variables

- 3.1. Binary dependent variables
- 3.2. Binary independent variables

4. Wrap up!



Today: *We start Econometrics!*

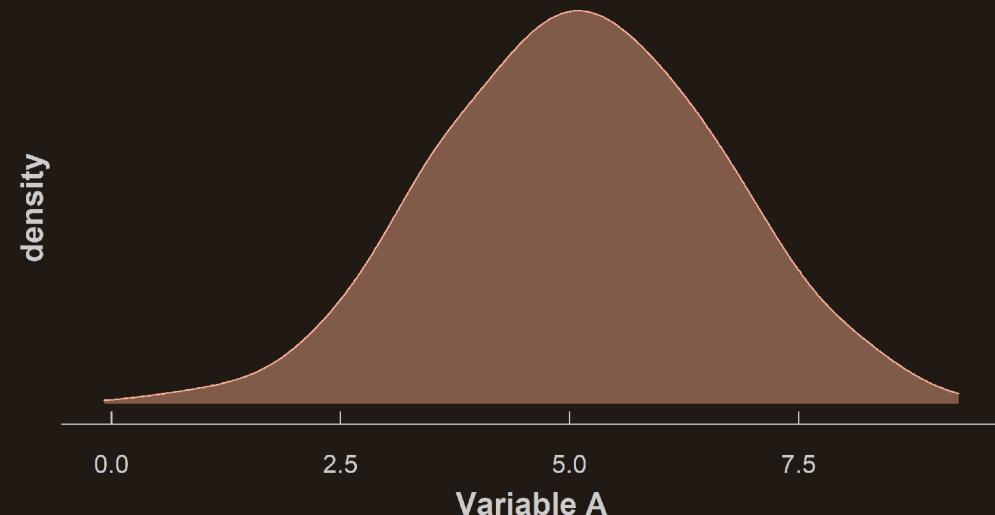
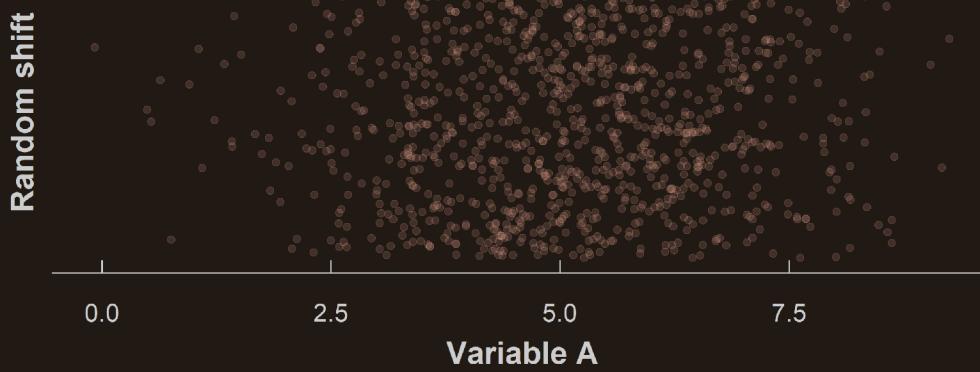
1. Joint distributions

- 1.1. Definition
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- 1.3. Correlation

1. Joint distributions

1.1. Definition

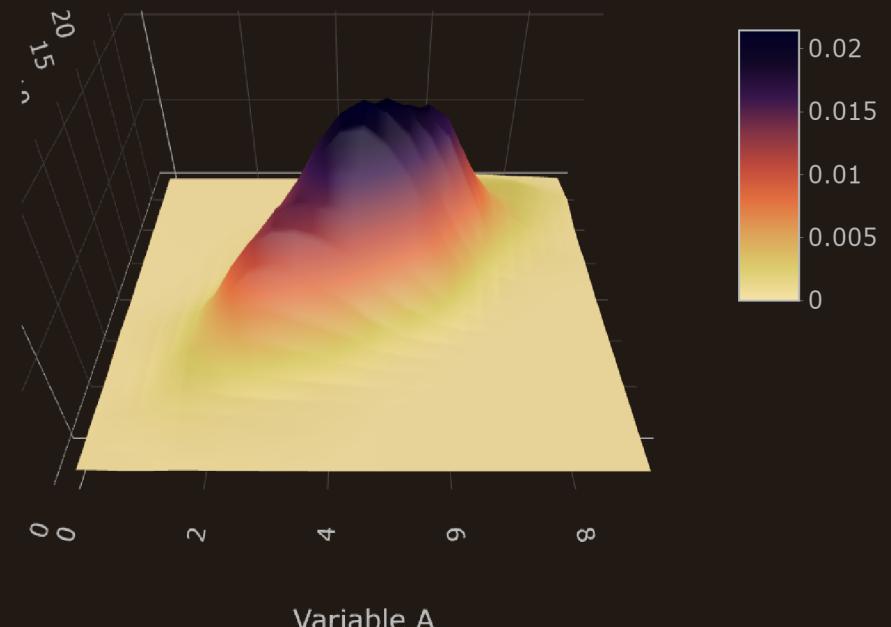
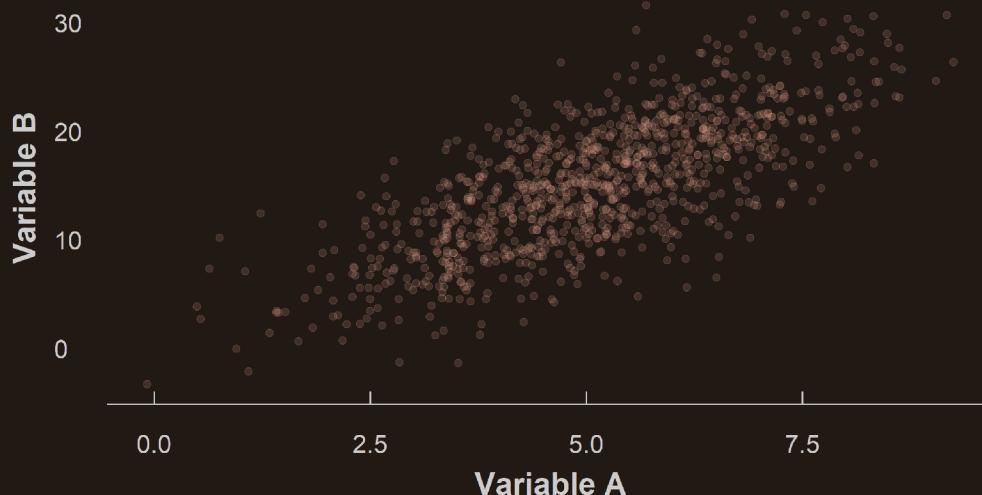
- The **joint distribution** shows the **values** and associated **frequencies** for **two variables** simultaneously
 - Remember how the **density** could represent the distribution of a **single variable**



1. Joint distributions

1.1. Definition

- The **joint distribution** shows the **values** and associated **frequencies** for **two variables** simultaneously
 - Remember how the **density** could represent the distribution of a **single variable**
 - The **joint density** can represent the joint distribution of **two variables**

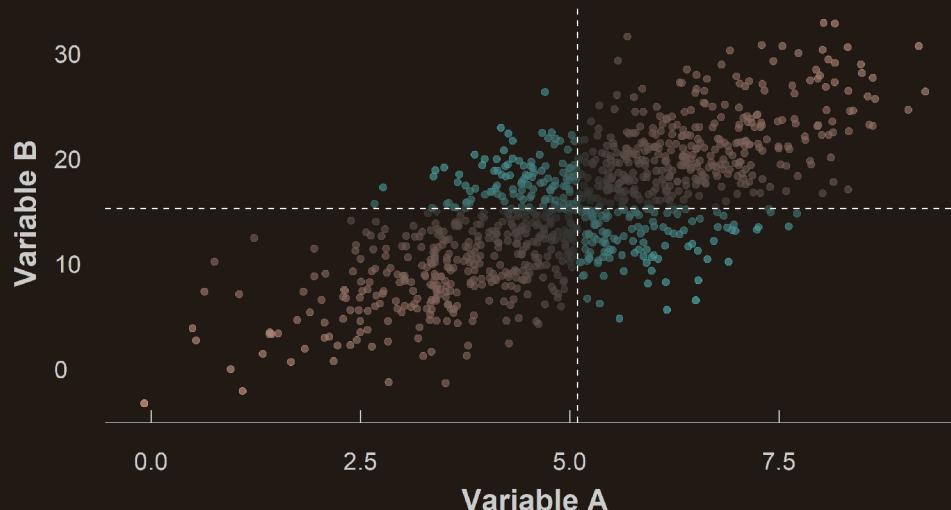


1. Joint distributions

1.2. Covariance

- 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**

$$\text{Cov}(x, y) = \frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})$$



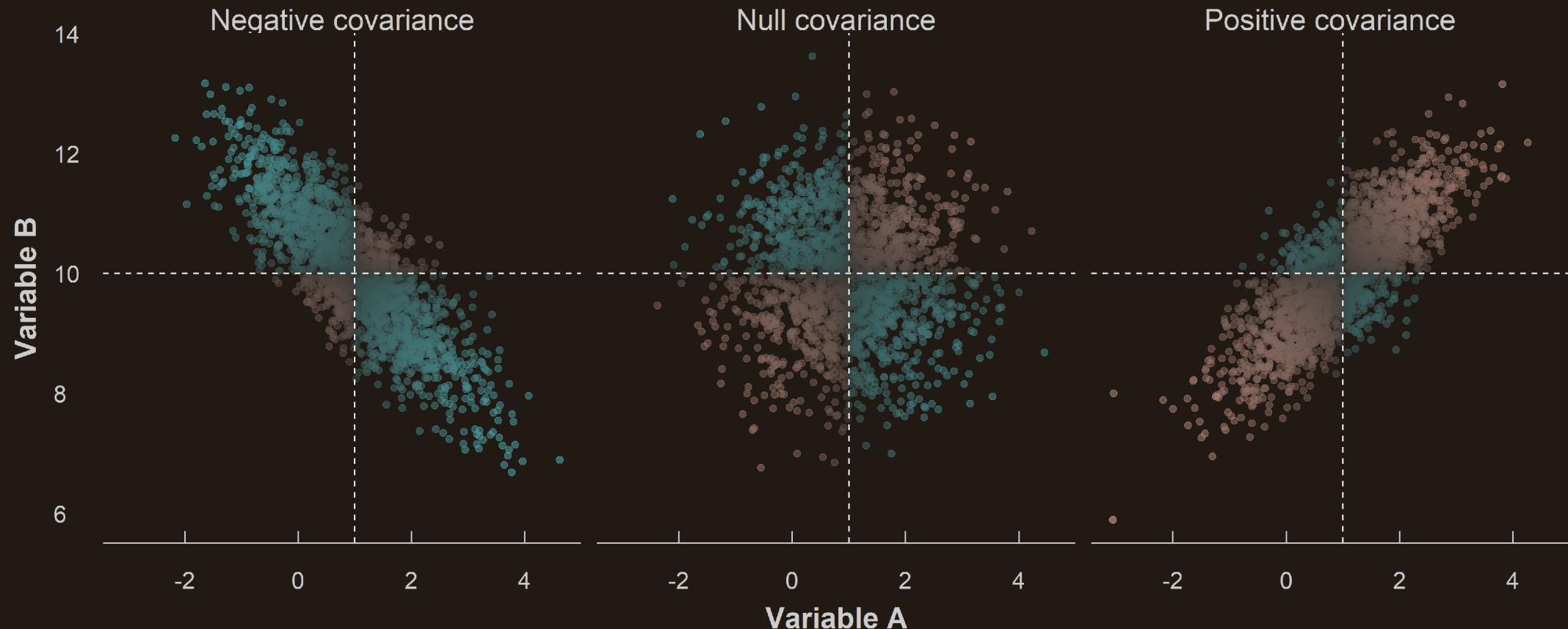
If y tends to be **large** relative to its mean when x is **large** relative to its mean, their **covariance is positive**

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



1. Joint distributions

1.2. Covariance





1. Joint distributions

1.2. Covariance

$$\text{Cov}(X, a) = 0$$

$$\text{Cov}(X, X) = \text{Var}(X)$$

$$\text{Cov}(X, Y) = \text{Cov}(Y, X)$$

$$\text{Cov}(aX, bY) = ab\text{Cov}(X, Y)$$

$$\text{Cov}(X + a, Y + b) = \text{Cov}(X, Y)$$

$$\begin{aligned}\text{Cov}(aX + bY, cW + dZ) &= ac\text{Cov}(X, W) + ad\text{Cov}(X, Z) + \\ &\quad bc\text{Cov}(Y, W) + bd\text{Cov}(Y, Z)\end{aligned}$$



1. Joint distributions

1.3. Correlation

- One disadvantage of the **covariance** is that it is **not standardized**
 - You **cannot** directly **compare** the covariance of two pairs of completely different variables
 - Given distance variables will have a larger covariance in centimeters than in meters
- Theoretically the **covariance** can take **values** from $-\infty$ to $+\infty$
- To **net out** the covariance from the **unit** of the data, we can **divide** it by $\text{SD}(x) \times \text{SD}(y)$
 - We call this **standardized** measure the **correlation**
 - Correlations coefficients are **comparable** because they are independent from the unit of the data

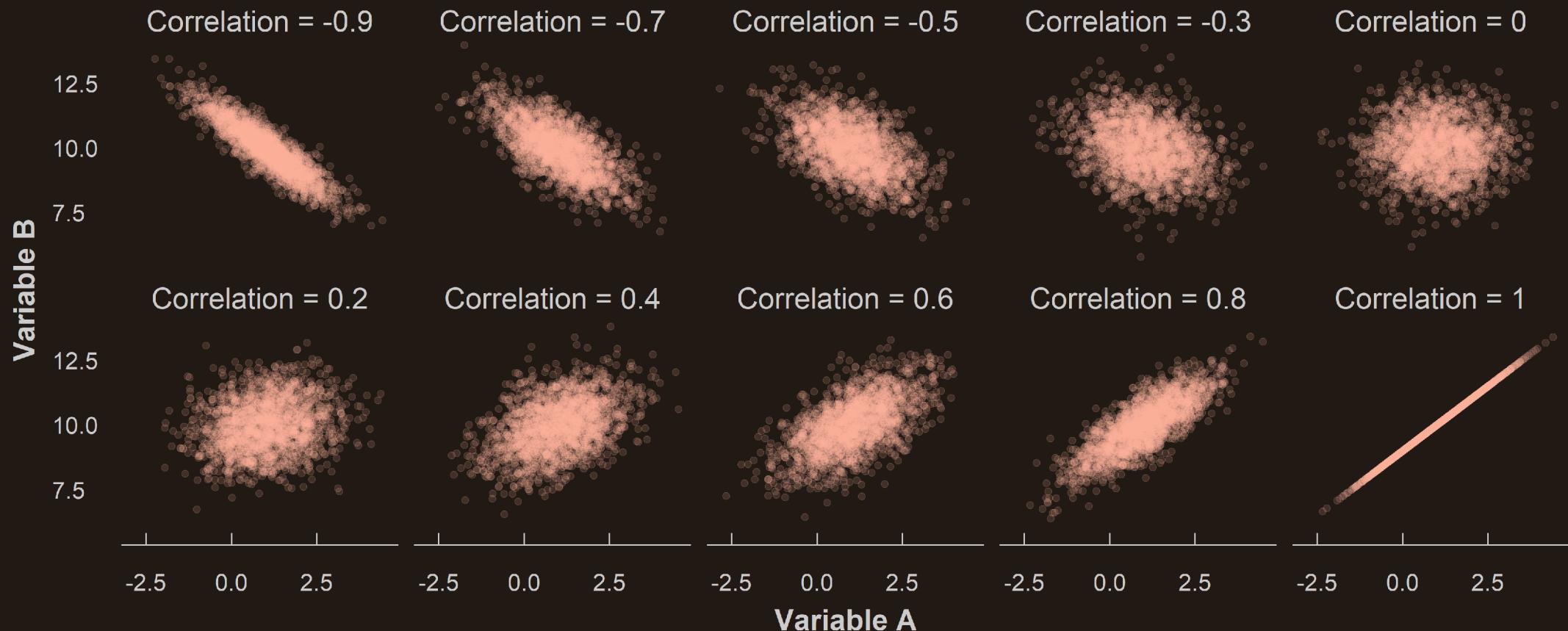
$$\text{Corr}(x, y) = \frac{\text{Cov}(x, y)}{\text{SD}(x) \times \text{SD}(y)}$$

→ The **correlation** coefficient is bounded between **values** from -1 to 1



1. Joint distributions

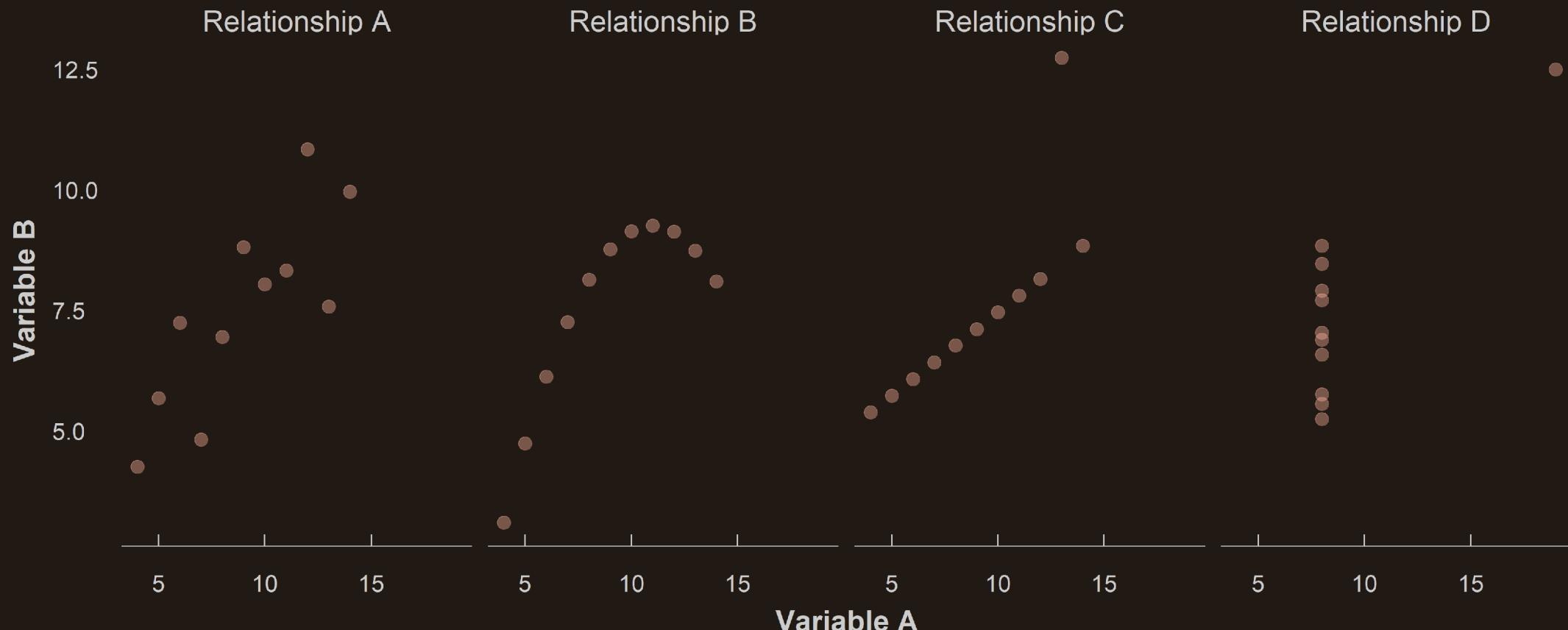
1.3. Correlation





1. Joint distributions

→ *But a same correlation can hide very different relationships*





1. Joint distributions

→ *Covariance and correlation in R*

```
x <- c(50, 70, 60, 80, 60)
y <- c(10, 30, 20, 30, 40)
```

- The **covariance** can be obtain with the function `cov()`

```
cov(x, y)
```

```
## [1] 70
```

- The **correlation** can be obtain with the function `cor()`

```
cor(x, y)
```

```
## [1] 0.5384615
```



Overview

1. Joint distributions ✓

- 1.1. Definition
- 1.2. Covariance
- 1.3. Correlation

2. Univariate regressions

- 2.1. Introduction to regressions
- 2.2. Coefficients estimation

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Overview

1. Joint distributions ✓

- 1.1. Definition
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2. Univariate regressions

2.1. Introduction to regressions

- Consider the following dataset

```
ggcurve <- read.csv("ggcurve.csv")
kable(head(ggcurve, 5), "First 5 rows")
```

First 5 rows		
country	ige	gini
Denmark	0.15	0.38
Norway	0.17	0.33
Finland	0.18	0.38
Canada	0.19	0.46
Australia	0.26	0.44

The data contains **2 variables** at the **country level**:

1. **IGE**: Intergenerational elasticity, which captures the % average increase in child income for a 1% increase in parental income

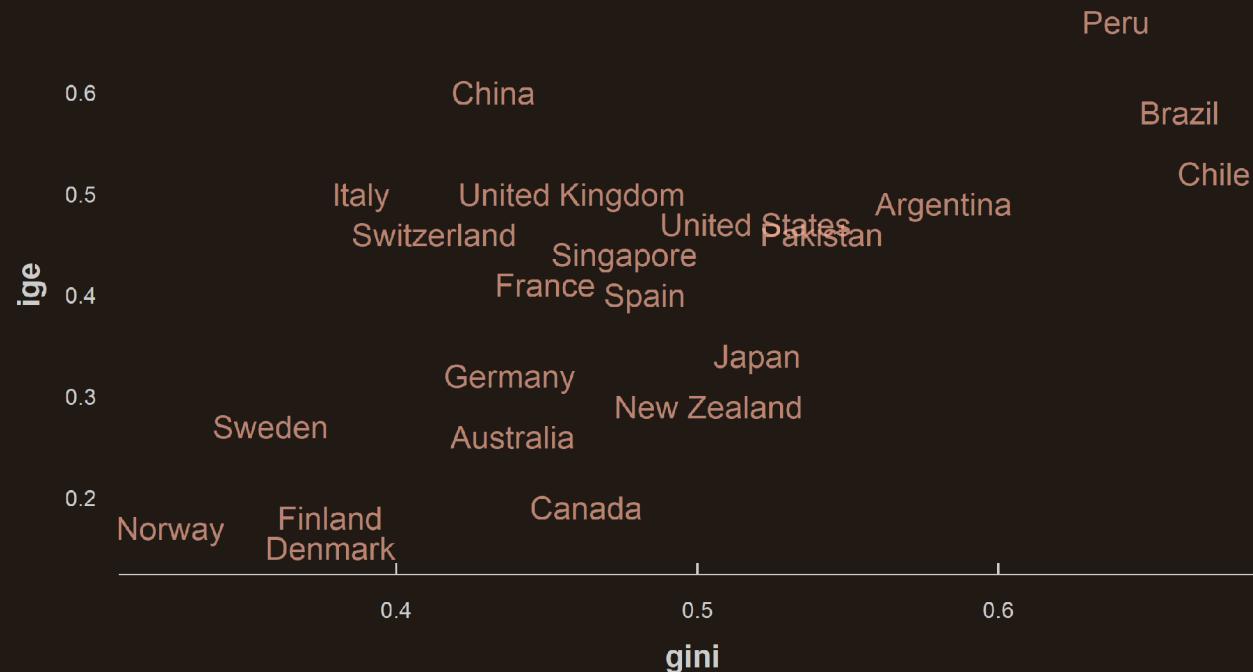
2. **Gini**: Gini index of income inequality between
0: everybody has the same income
1: a single individual has all the income

2. Univariate regressions

2.1. Introduction to regressions

- To investigate the **relationship** between these two variables we can start with a **scatterplot**

```
ggplot(ggcurve , aes(x = gini, y = ige, label = country)) + geom_text()
```





2. Univariate regressions

2.1. Introduction to regressions

- We see that the two variables are **positively correlated** with each other:
 - When **one** tends to be **high** relative to its mean, **the other as well**
 - When **one** tends to be **low** relative to its mean, **the other as well**

```
cor(ggcurve$gini, ggcurve$ige)
```

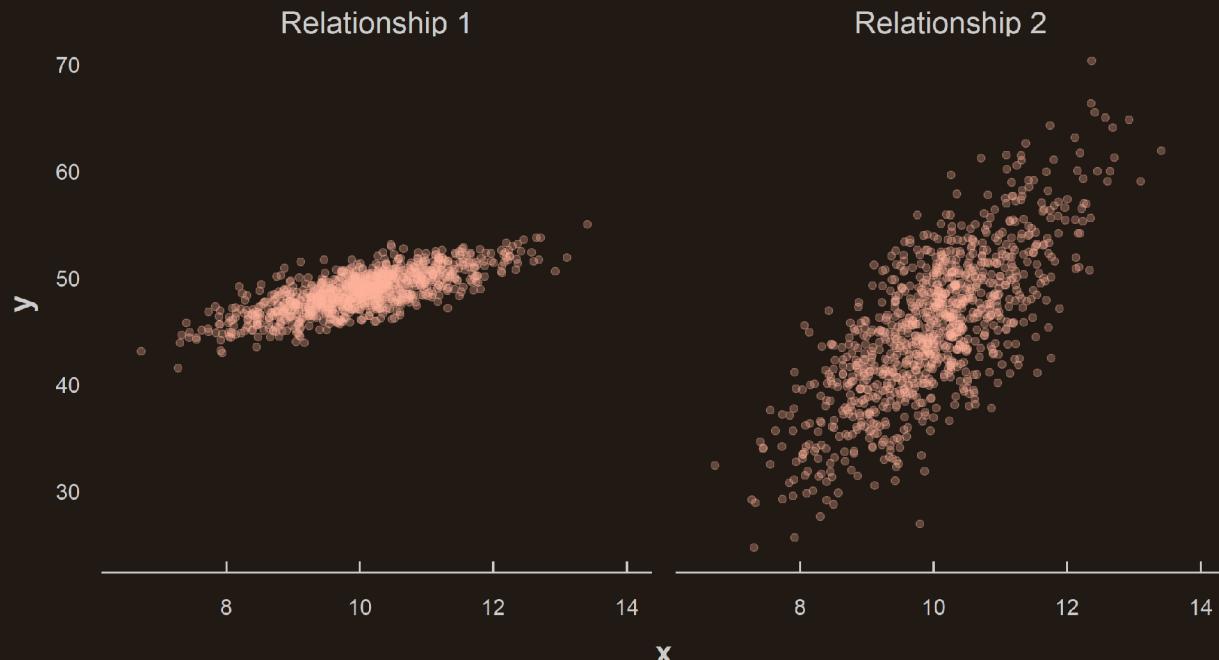
```
## [1] 0.6517277
```

- The **correlation** coefficient is equal to **.65**
 - Remember that the correlation can take values from -1 to 1
 - Here the correlation is indeed **positive** and **fairly strong**
- But how useful is this for real-life applications? We may want more **practical** information:
 - Like by how much y is **expected to increase** for a given change in x
 - This is of particular interest for economists and **policy** makers

2. Univariate regressions

2.1. Introduction to regressions

- Consider these two relationships :



→ One is less noisy but flatter

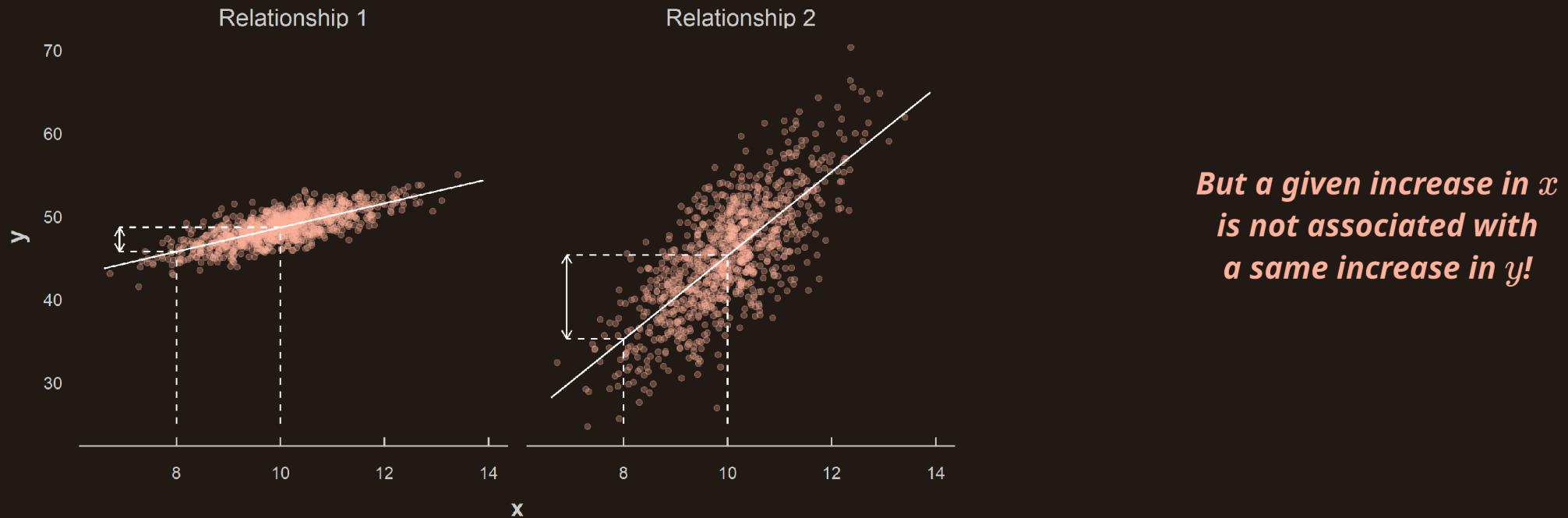
→ One is noisier but steeper

Both have a correlation of .75

2. Univariate regressions

2.1. Introduction to regressions

- Consider these two relationships :





2. Univariate regressions

2.1. Introduction to regressions

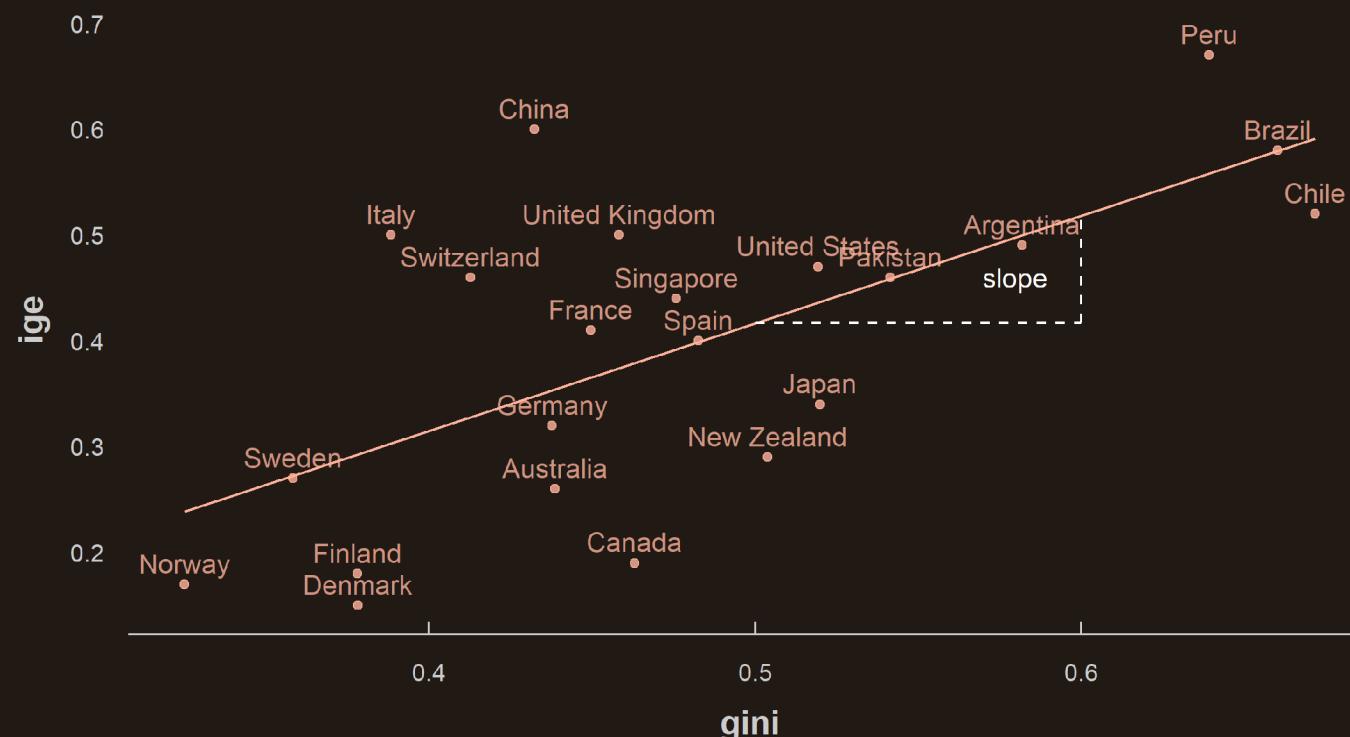
- Knowing that income inequality is **negatively correlated** with intergenerational mobility is one thing
- But how much more intergenerational mobility could we expect for a given reduction in inequality?
 - We need to characterize the "**steepness**" of the relationship!
- It is usually the **type of questions** we're interested in:
 - *How much more should I expect to earn for an additional year of education?*
 - *By how many years would life expectancy be expected to decrease for a given increase in air pollution?*
 - *By how much would test scores increase for a given decrease in the number of students per teacher?*
- And once again, this is typically what is of interest for **policymakers**

→ **But how to compute this expected change in y for a given change of x ?**

2. Univariate regressions

2.2. Coefficients estimation

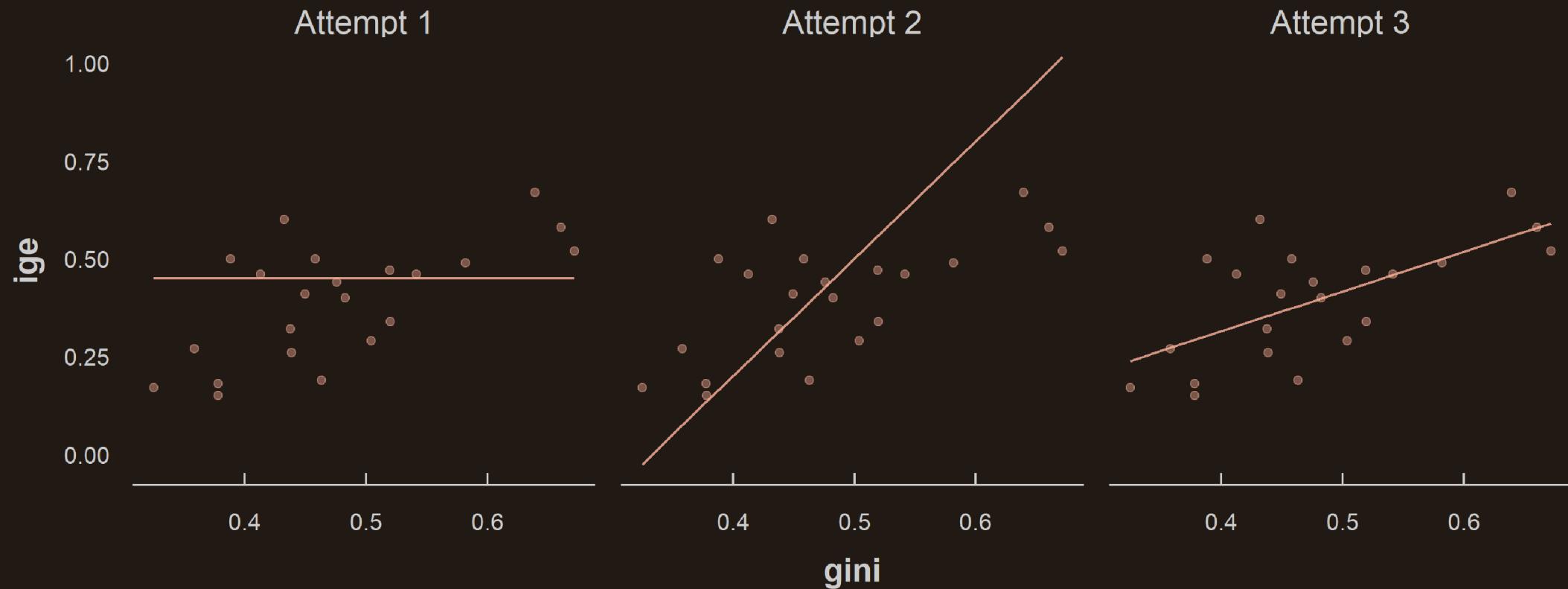
- The idea is to find the **line that fits the data** the best
 - Such that its **slope** can indicate how we **expect y to change** if we **increase x by 1 unit**



2. Univariate regressions

2.2. Coefficients estimation

- But how do we **find that line?**

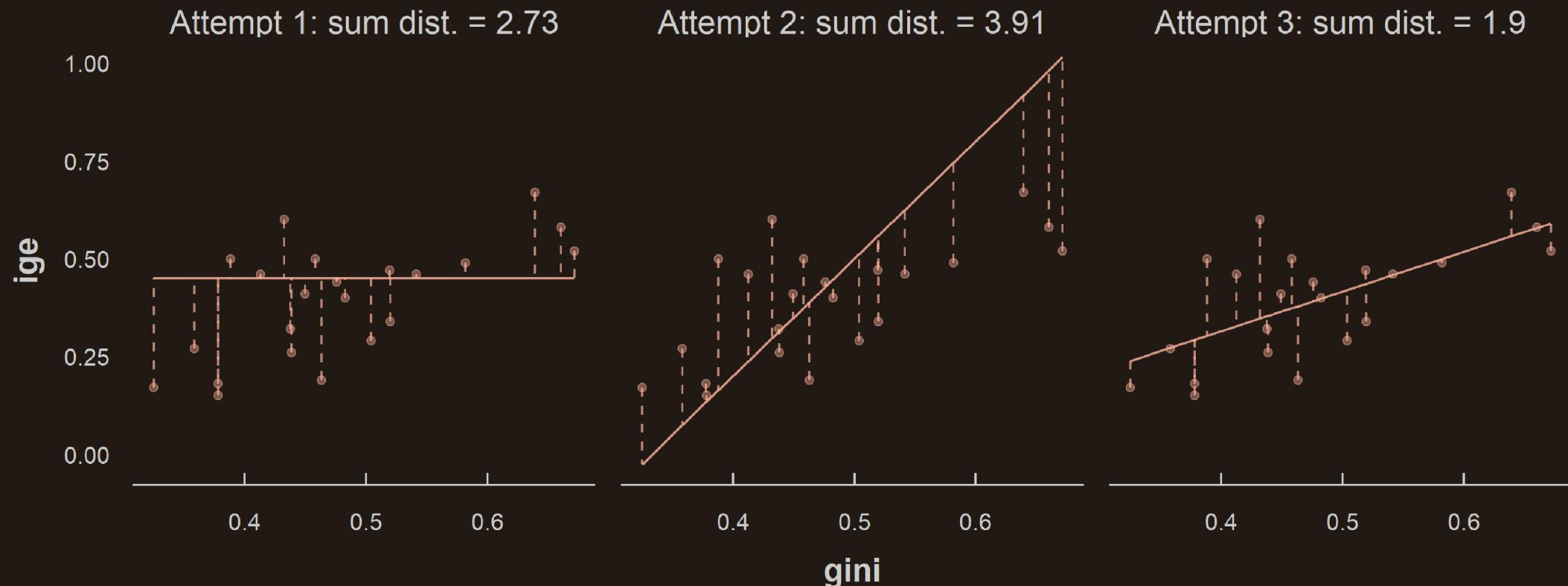




2. Univariate regressions

2.2. Coefficients estimation

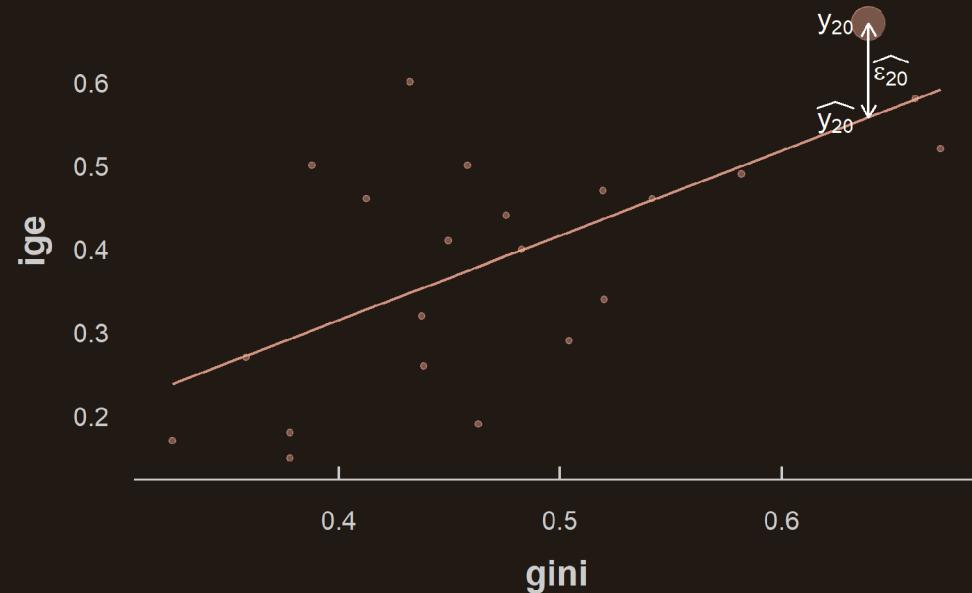
- We try to **minimize the distance** between each point and our line



2. Univariate regressions

2.2. Coefficients estimation

Take for instance the 20th observation: Peru



And consider the following **notations**:

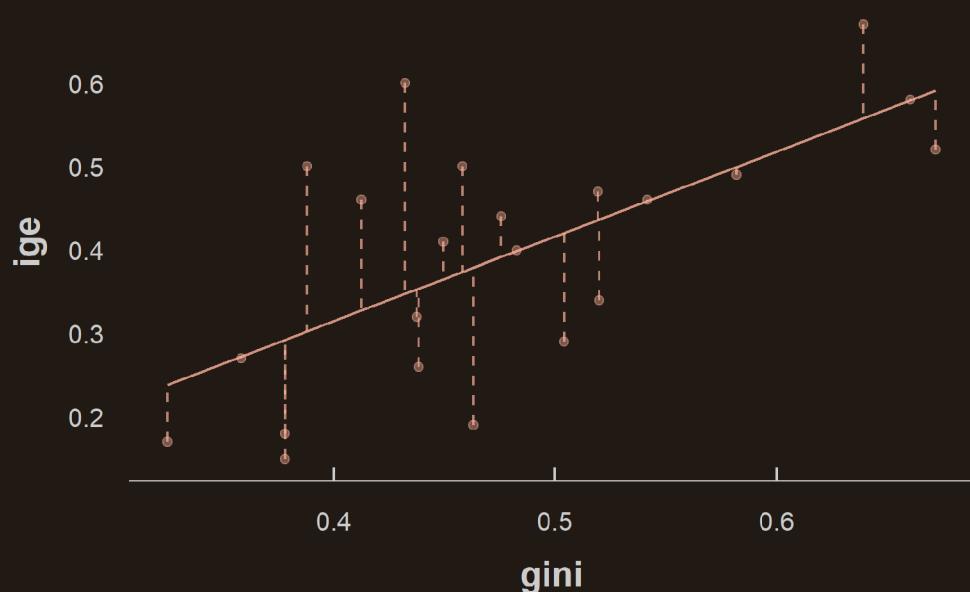
- We denote y_i the ige of the i^{th} country
- We denote x_i the gini of the i^{th} country
- We denote \hat{y}_i the value of the y coordinate of our line for $x = x_i$

→ The distance between the i^{th} y value and the line is
$$y_i - \hat{y}_i$$

- We label that distance $\hat{\epsilon}_i$

2. Univariate regressions

2.2. Coefficients estimation



- $\hat{\varepsilon}_i$ being the distance between a point y_i and its corresponding value on the line \hat{y}_i , we can write:

$$y_i = \hat{y}_i + \hat{\varepsilon}_i$$

- And because \hat{y}_i is a **straight line**, it can be expressed as

$$\hat{y}_i = \hat{\alpha} + \hat{\beta}x_i$$

- Where:
 - $\hat{\alpha}$ is the **intercept**
 - $\hat{\beta}$ is the **slope**

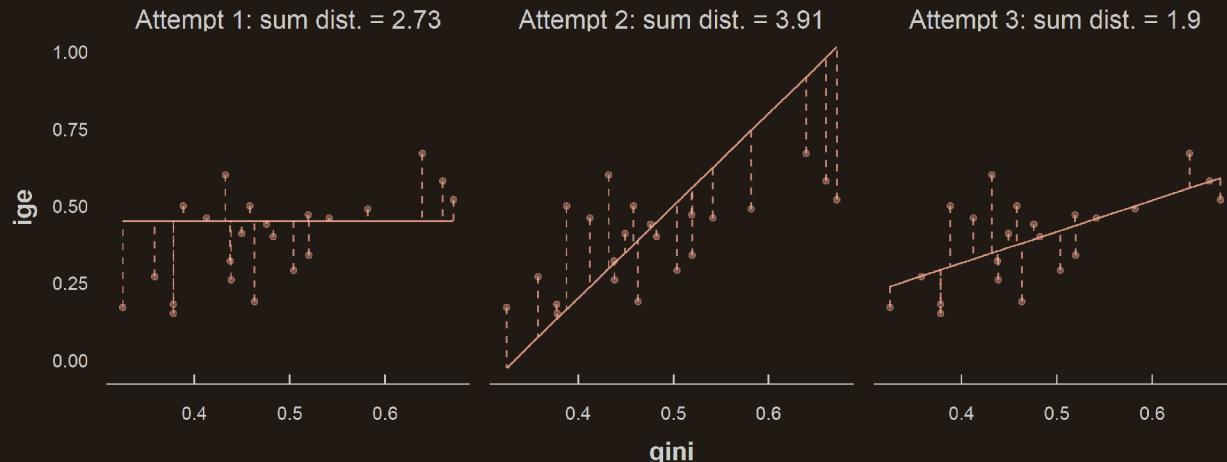
2. Univariate regressions

2.2. Coefficients estimation

- Combining these two **definitions** yields the equation:

$$y_i = \hat{\alpha} + \hat{\beta}x_i + \hat{\varepsilon}_i \begin{cases} y_i = \hat{y}_i + \hat{\varepsilon}_i & \text{Definition of distance} \\ \hat{y}_i = \hat{\alpha} + \hat{\beta}x_i & \text{Definition of the line} \end{cases}$$

- Depending on the values of $\hat{\alpha}$ and $\hat{\beta}$, the value of every $\hat{\varepsilon}_i$ will change



Attempt 1: $\hat{\alpha}$ is too high and $\hat{\beta}$ is too low $\rightarrow \hat{\varepsilon}_i$ are large

Attempt 2: $\hat{\alpha}$ is too low and $\hat{\beta}$ is too high $\rightarrow \hat{\varepsilon}_i$ are large

Attempt 3: both $\hat{\alpha}$ and $\hat{\beta}$ seem right $\rightarrow \hat{\varepsilon}_i$ are low



2. Univariate regressions

2.2. Coefficients estimation

- We want to find the values of $\hat{\alpha}$ and $\hat{\beta}$ that **minimize** the overall **distance** between the points and the line

$$\min_{\hat{\alpha}, \hat{\beta}} \sum_{i=1}^n \hat{\varepsilon}_i^2$$

- Note that we square $\hat{\varepsilon}_i$ to avoid that its positive and negative values compensate
- This method is what we call **Ordinary Least Squares (OLS)**
- To solve this **optimization problem**, we need to express $\hat{\varepsilon}_i$ it in terms of alpha $\hat{\alpha}$ and $\hat{\beta}$

$$y_i = \hat{\alpha} + \hat{\beta}x_i + \hat{\varepsilon}_i$$

\iff

$$\hat{\varepsilon}_i = y_i - \hat{\alpha} - \hat{\beta}x_i$$



2. Univariate regressions

2.2. Coefficients estimation

- And our minimization problem writes

$$\min_{\hat{\alpha}, \hat{\beta}} \sum_{i=1}^n (y_i - \hat{\alpha} - \hat{\beta}x_i)^2$$

$$\frac{\partial}{\partial \hat{\alpha}} = 0 \iff -2 \sum_{i=1}^n (y_i - \hat{\alpha} - \hat{\beta}x_i) = 0$$

$$\frac{\partial}{\partial \hat{\beta}} = 0 \iff -2x_i \sum_{i=1}^n (y_i - \hat{\alpha} - \hat{\beta}x_i) = 0$$

- Rearranging the first equation yields

$$\sum_{i=1}^n y_i - n\hat{\alpha} - \sum_{i=1}^n \hat{\beta}x_i = 0 \iff \hat{\alpha} = \bar{y} - \hat{\beta}\bar{x}$$



2. Univariate regressions

2.2. Coefficients estimation

- Replacing $\hat{\alpha}$ in the second equation by its new expression writes

$$-2x_i \sum_{i=1}^n (y_i - \hat{\alpha} - \hat{\beta}x_i) = 0 \iff -2x_i \sum_{i=1}^n \left[y_i - (\bar{y} - \hat{\beta}\bar{x}) - \hat{\beta}x_i \right] = 0$$

- And by rearranging the terms we obtain

$$\hat{\beta} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

- Notice that multiplying the nominator and the denominator by $1/n$ yields:

$$\hat{\beta} = \frac{\text{Cov}(x_i, y_i)}{\text{Var}(x_i)} \quad ; \quad \hat{\alpha} = \bar{y} - \frac{\text{Cov}(x_i, y_i)}{\text{Var}(x_i)} \times \bar{x}$$

Practice

10 : 00

1) Import `ggcurve.csv` and compute the $\hat{\alpha}$ and $\hat{\beta}$ coefficients of that equation:

$$\text{gini}_i = \hat{\alpha} + \hat{\beta} \times \text{IGE}_i + \hat{\varepsilon}_i$$

2) Create a new variable in the dataset for $\widehat{\text{gini}}$

3) Plot your results (scatter plot + line)

Hints: You can use different y variables for different geometries by specifying the mapping within the geometry function:
`geom_point(aes(y = y))`

$$\hat{\beta} = \frac{\text{Cov}(x_i, y_i)}{\text{Var}(x_i)}$$

$$\hat{\alpha} = \bar{y} - \frac{\text{Cov}(x_i, y_i)}{\text{Var}(x_i)} \times \bar{x}$$

You've got 10 minutes!

Solution

1) Import `ggcurve.csv` and compute the $\hat{\alpha}$ and $\hat{\beta}$ coefficients of that equation:

```
# Read the data
ggcurve <- read.csv("ggcurve.csv")
# Compute beta
beta <- cov(ggcurve$gini, ggcurve$ige) / var(ggcurve$gini)
# Compute alpha
alpha <- mean(ggcurve$ige) - (beta * mean(ggcurve$gini))
```

```
c(alpha, beta)
```

```
## [1] -0.09129311  1.01546204
```

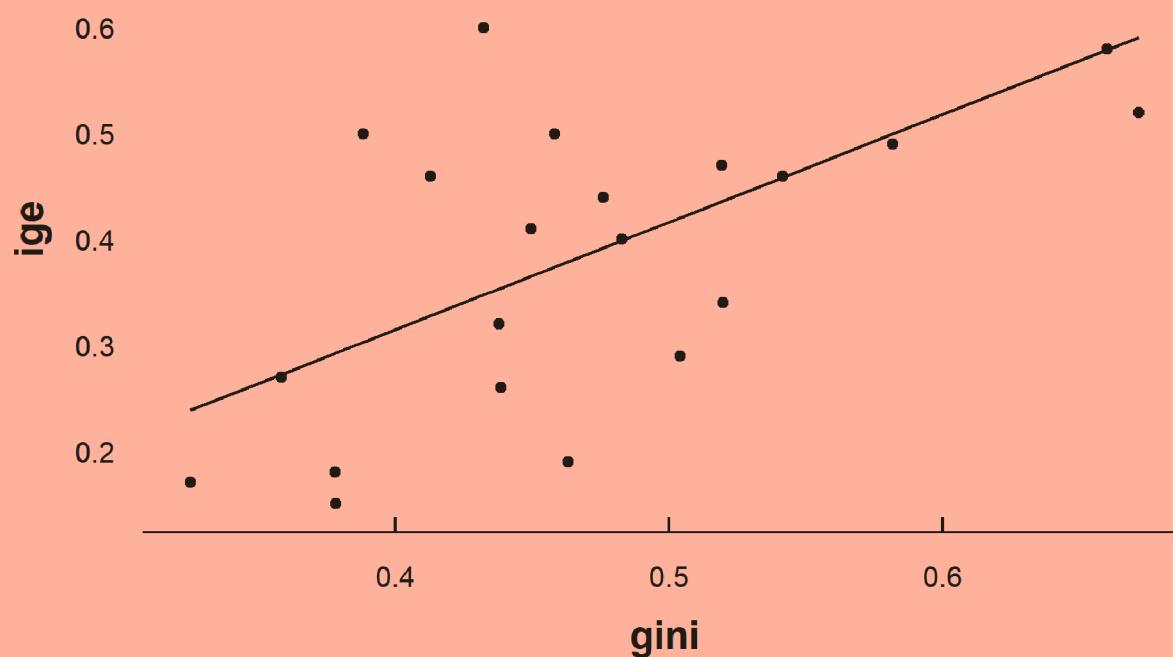
2) Create a new variable in the dataset for \widehat{gini}

```
ggcurve <- ggcurve %>%
  mutate(fit = alpha + beta * gini)
```

Solution

3) Plot your results (scatter plot + line)

```
ggplot(ggcurve, aes(x = gini)) +  
  geom_point(aes(y = ige)) + geom_line(aes(y = fit))
```



2. Univariate regressions

2.2. Coefficients estimation

- As usual there are **functions** to do that **in R**

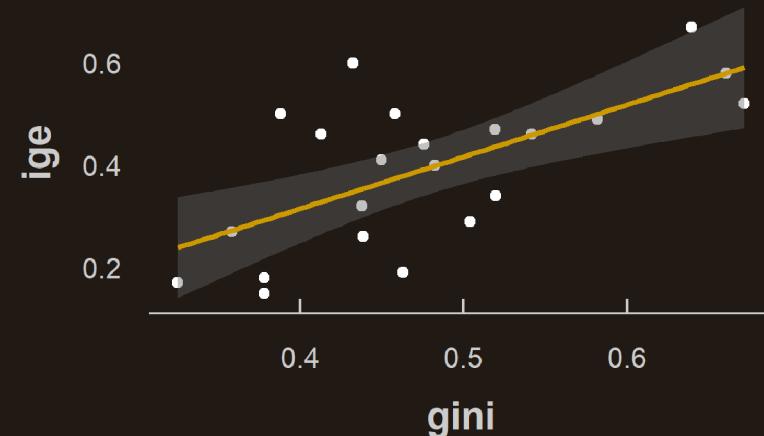
- lm()** to estimate regression coefficients
- It has two main **arguments**:
 - Formula**: written as $y \sim x$
 - Data**: where y and x are

```
lm(ige ~ gini, ggcurve)
```

```
##  
## Call:  
## lm(formula = ige ~ gini, data = ggcurve)  
##  
## Coefficients:  
## (Intercept)      gini  
## -0.09129     1.01546
```

- geom_smooth()** to plot the fit

```
ggplot(ggcurve, aes(x = gini, y = ige)) +  
  geom_point() +  
  geom_smooth(method = "lm", formula = y ~ x)
```



Vocabulary

- This equation we're working on is called a **regression model**

$$y_i = \hat{\alpha} + \hat{\beta}x_i + \hat{\varepsilon}_i$$

- We say that we **regress y on x** to find the coefficients $\hat{\alpha}$ and $\hat{\beta}$ that characterize the regression line
- We often call $\hat{\alpha}$ and $\hat{\beta}$ **parameters** of the regression because we tune them to fit our model to the data
- We also have different names for the x and y variables
 - y is called the **dependent** or **explained** variable
 - x is called the **independent** or **explanatory** variable
- We call $\hat{\varepsilon}_i$ the **residuals** because it is what is left after we fitted the data the best we could
- And $\hat{y}_i = \hat{\alpha} + \hat{\beta}x_i$, i.e., the value on the regression line for a given x_i are called the **fitted values**



Overview

1. Joint distributions ✓

- 1.1. Definition
- 1.2. Covariance
- 1.3. Correlation

2. Univariate regressions ✓

- 2.1. Introduction to regressions
- 2.2. Coefficients estimation

3. Binary variables

- 3.1. Binary dependent variables
- 3.2. Binary independent variables

4. Wrap up!



Overview

1. Joint distributions ✓

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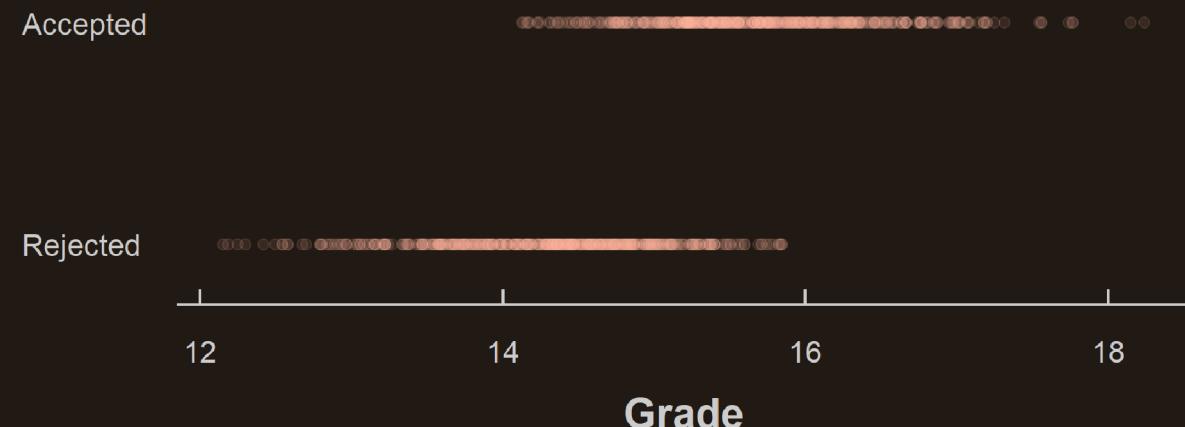
- 3.1. Binary dependent variables
- 3.2. Binary independent variables



3. Binary variables

3.1. Binary dependent variables

- So far we've considered only **continuous variables** in our regression models
 - But what if our **dependent** variable is **discrete**?
- Consider that we have data on candidates to a job:
 - Their *Baccalauréat* grade (/20)
 - Whether they got accepted

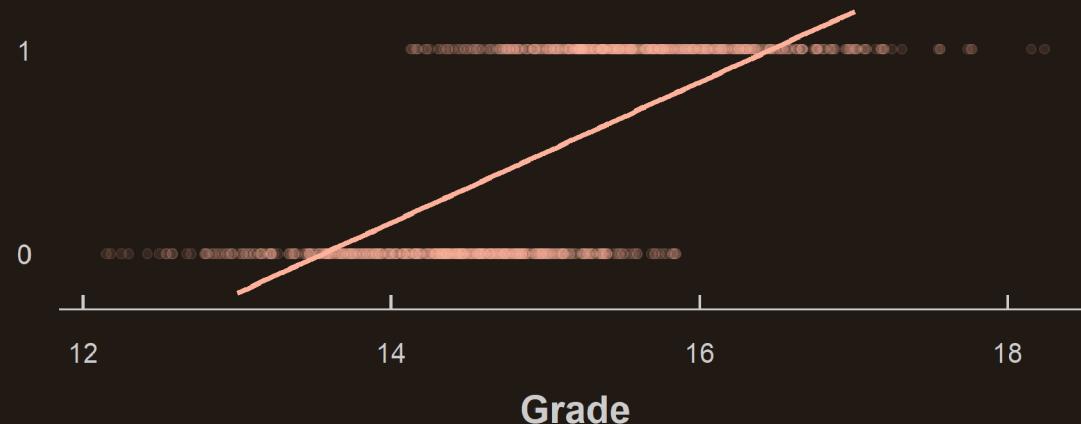


3. Binary variables

3.1. Binary dependent variables

- Even if the **outcome variable** is binary we can regress it on the grade variable
 - We can convert it into a **dummy** variable, a variable taking either the value **0 or 1**
 - Here consider a dummy variable taking the value 1 if the person was accepted

$$\mathbb{1}\{y_i = \text{Accepted}\} = \hat{\alpha} + \hat{\beta} \times \text{Grade}_i + \hat{\varepsilon}_i$$

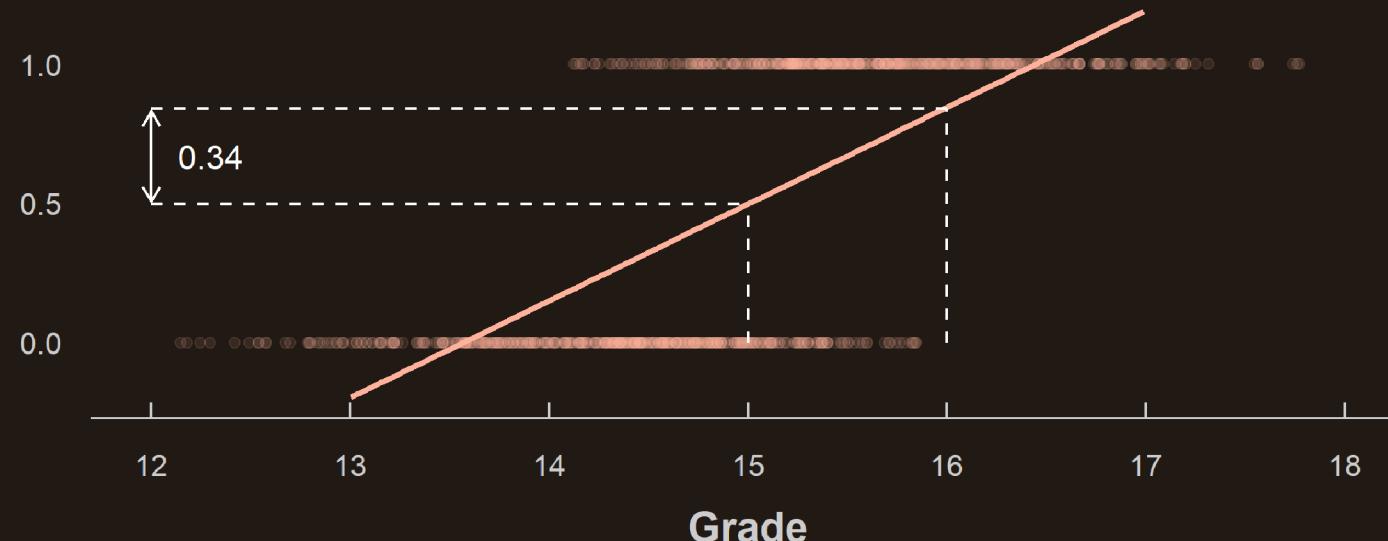


→ How would you interpret the beta coefficient from this regression?

3. Binary variables

3.1. Binary dependent variables

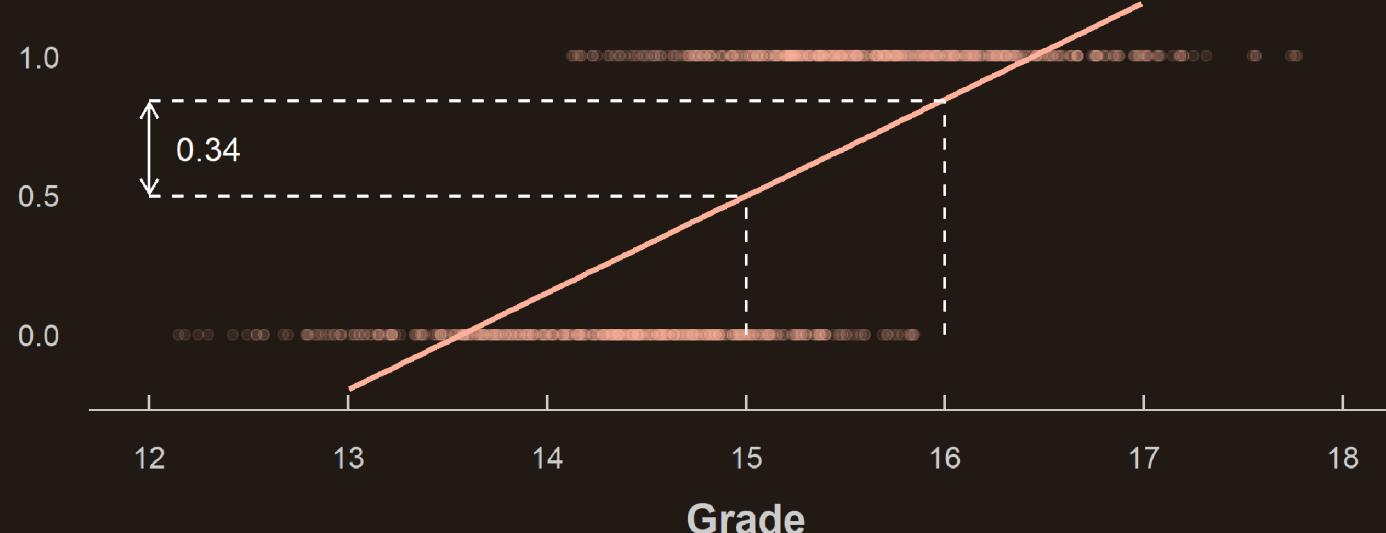
- The **fitted values** can be viewed as the **probability** to be accepted for a given grade
 - $\hat{\beta}$ is thus by how much this probability would vary on expectation for a 1 point increase in the grade
 - That's why we call OLS regression models with a binary outcome **Linear Probability Models**



3. Binary variables

3.1. Binary dependent variables

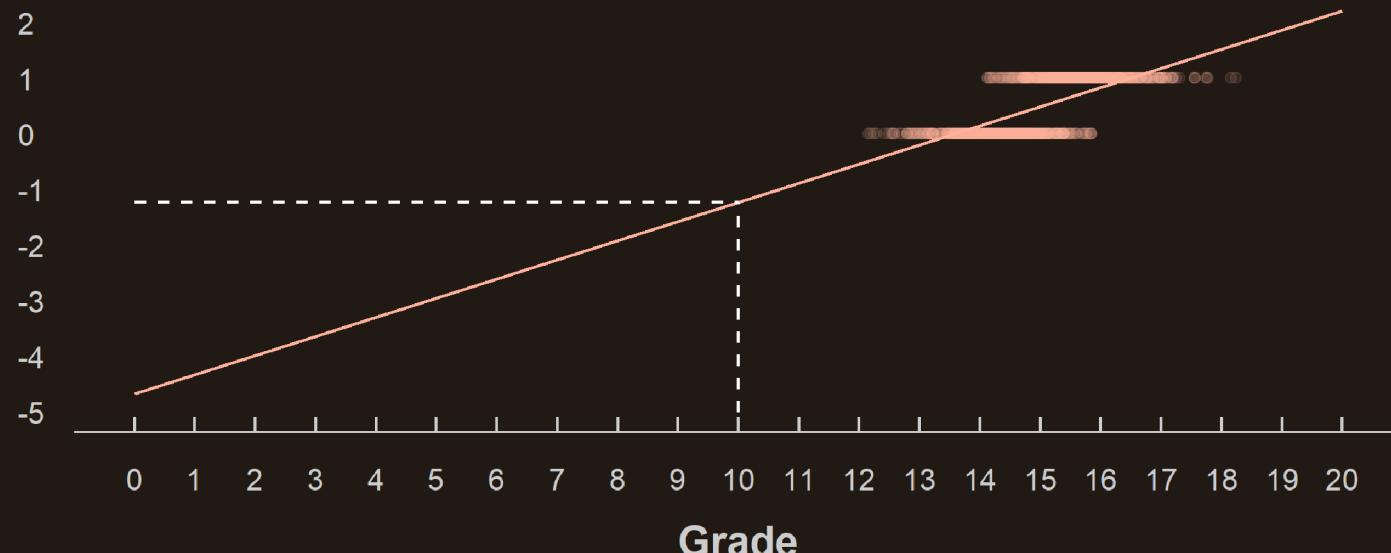
- But what kind of **problems** could we encounter with **such models**?
 - What would be the $\hat{\alpha}$ coefficient here?
 - And what's the probability to be accepted for a grade of 18?



3. Binary variables

3.1. Binary dependent variables

- With an **LPM** you can end up with "**probabilities**" that are **lower than 0** and **greater than 1**
 - Interpretation** is only **valid** for values of x sufficiently **close to the mean**
 - Keep that in mind and be **careful** when interpreting the results of an LPM





3. Binary variables

3.2. Binary independent variables

- Now consider that we have individual **data** containing
 - The **sex**
 - The **height** (centimeters)

- So the situation is different
 - We used to have a **binary dependent variable**:

$$1\{y_i = \text{Accepted}\} = \hat{\alpha} + \hat{\beta} \times \text{Grade}_i + \hat{\varepsilon}_i$$

- We now have a **binary independent variable**:

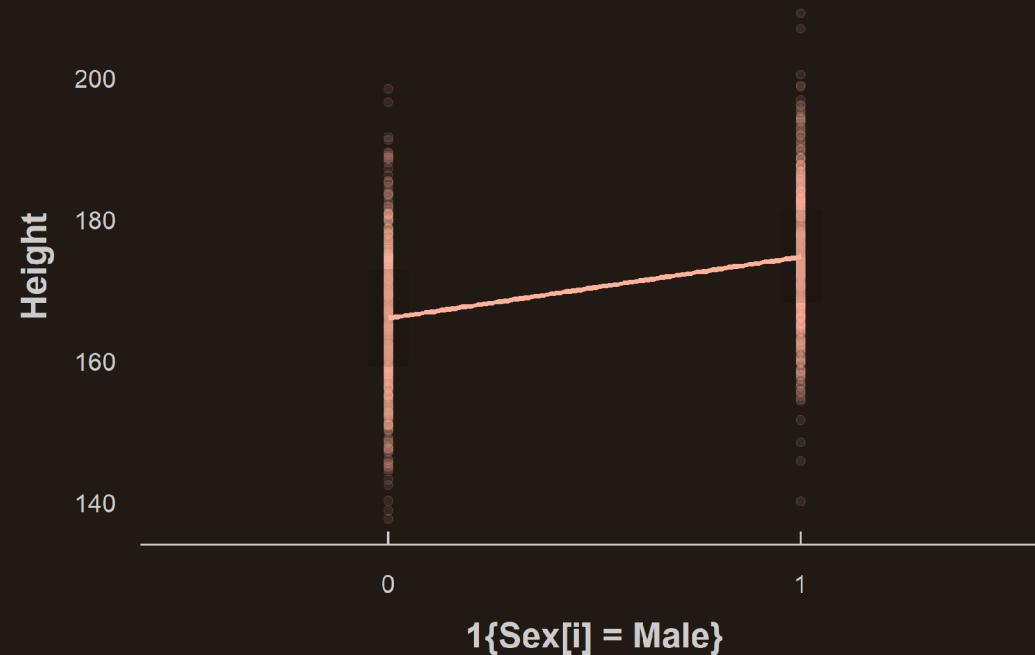
$$\text{Height}_i = \hat{\alpha} + \hat{\beta} \times 1\{\text{Sex}_i = \text{Male}\} + \hat{\varepsilon}_i$$

→ How would you interpret the coefficient $\hat{\beta}$ from this regression?

3. Binary variables

3.2. Binary independent variables

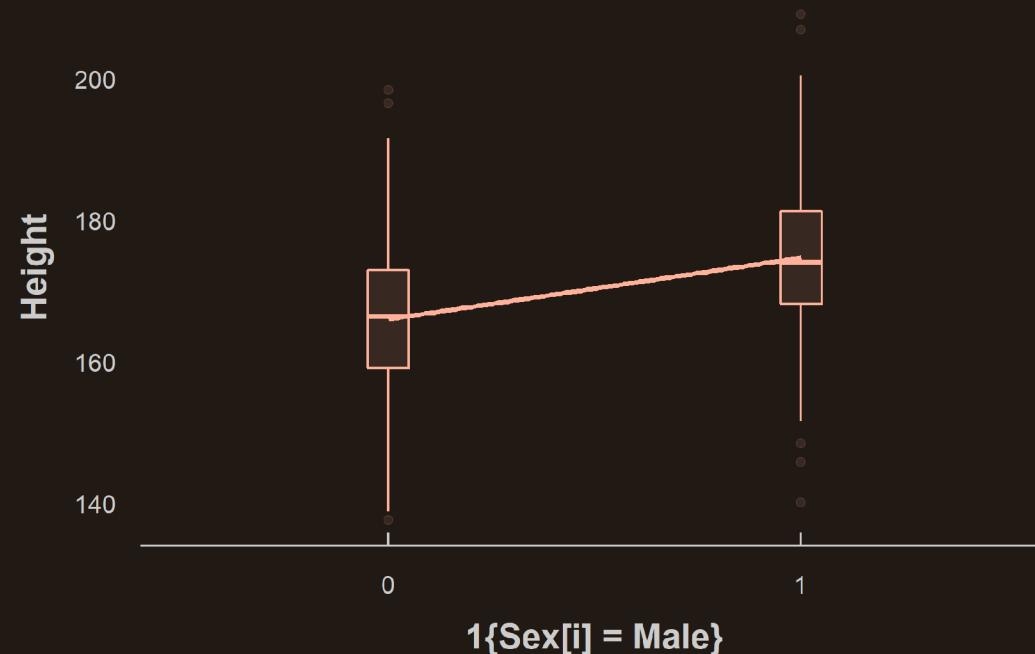
- If the sex variable was **continuous** it would be the expected increase in height for a "**1 unit increase**" in sex
 - Here the "**1 unit increase**" is switching from 0 to 1, i.e. **from female to male**
 - With that in mind, how would you interpret the coefficient $\hat{\beta}$?



3. Binary variables

3.2. Binary independent variables

- If I replace the point geometry by the corresponding **boxplots**
 - What this "**1 unit increase**" corresponds to should be **clearer**
 - The coefficient $\hat{\beta}$ is actually the **difference** between the **average height** for males and females



3. Binary variables

3.2. Binary independent variables

$$\overline{\text{Height}}_{[\text{Sex}_i = \text{Female}]} = 165$$

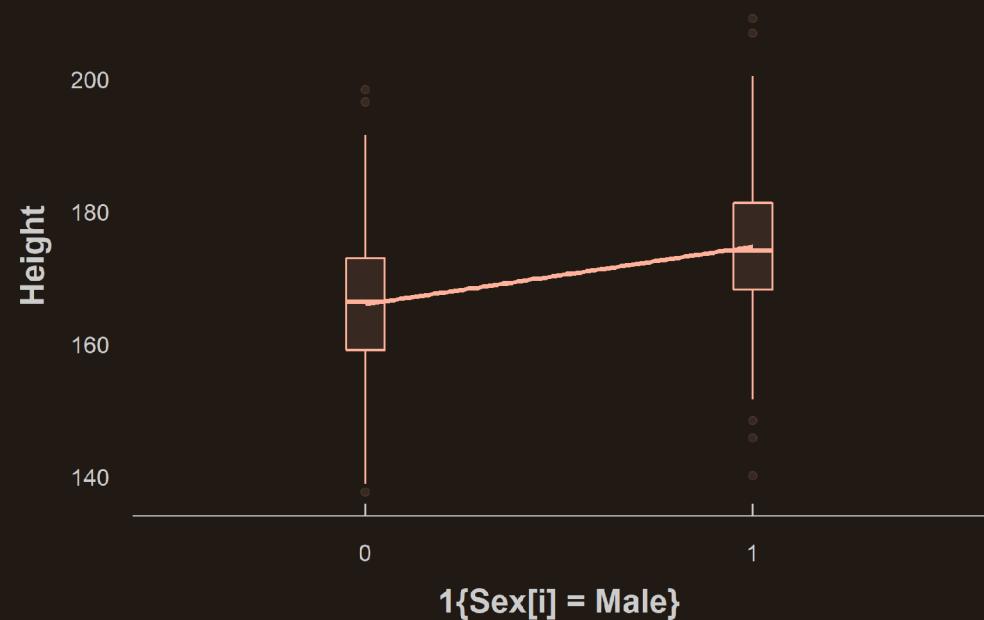
$$\overline{\text{Height}}_{[\text{Sex}_i = \text{Male}]} = 176$$

$$\text{Height}_i = \hat{\alpha} + \hat{\beta} \times 1\{\text{Sex}_i = \text{Male}\} + \hat{\varepsilon}_i$$

$$\hat{\alpha} = 165 \quad \hat{\beta} = 11$$

$$\text{Height}_i = \hat{\alpha} + \hat{\beta} \times 1\{\text{Sex}_i = \text{Female}\} + \hat{\varepsilon}_i$$

$$\hat{\alpha} = 176 \quad \hat{\beta} = -11$$





3. Binary variables

3.2. Binary independent variables

- In terms of **fitted values**:

$$\text{Height}_i = \hat{\alpha} + \hat{\beta} \times 1\{\text{Sex}_i = \text{Male}\} + \hat{\varepsilon}_i$$

- We now have $\hat{\alpha}$ and $\hat{\beta}$:

$$\text{Height}_i = 165 + 11 \times 1\{\text{Sex}_i = \text{Male}\} + \hat{\varepsilon}_i$$

- The fitted values write:

$$\widehat{\text{Height}}_i = 165 + 11 \times 1\{\text{Sex}_i = \text{Male}\}$$

- When the dummy equals 0 (*females*):

$$\begin{aligned}\widehat{\text{Height}}_i &= 165 + 11 \times 0 \\ &= 165 = \overline{\text{Height}}_{[\text{Sex}_i=\text{Female}]}\end{aligned}$$

- When the dummy equals 1 (*males*):

$$\begin{aligned}\widehat{\text{Height}}_i &= 165 + 11 \times 1 \\ &= 176 = \overline{\text{Height}}_{[\text{Sex}_i=\text{Male}]}\end{aligned}$$



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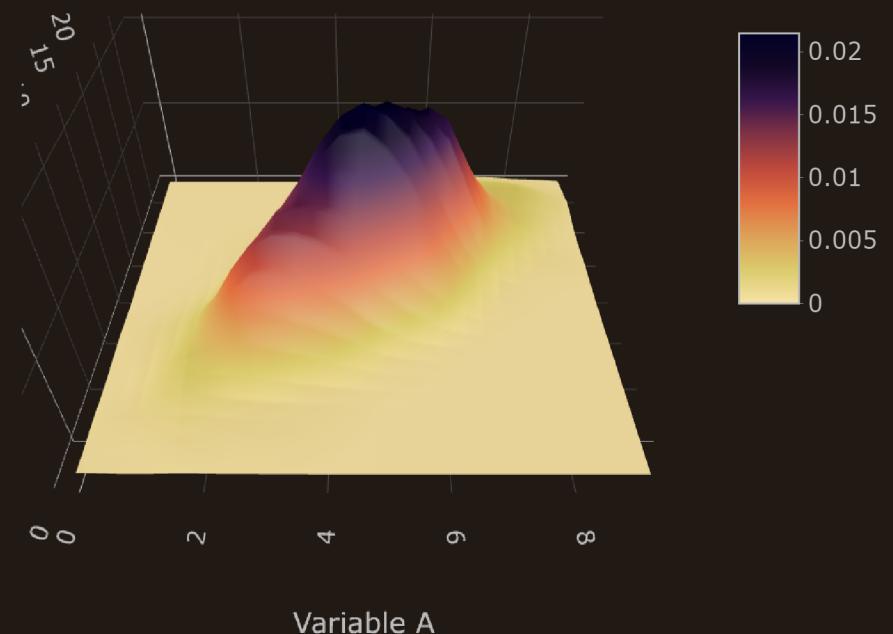
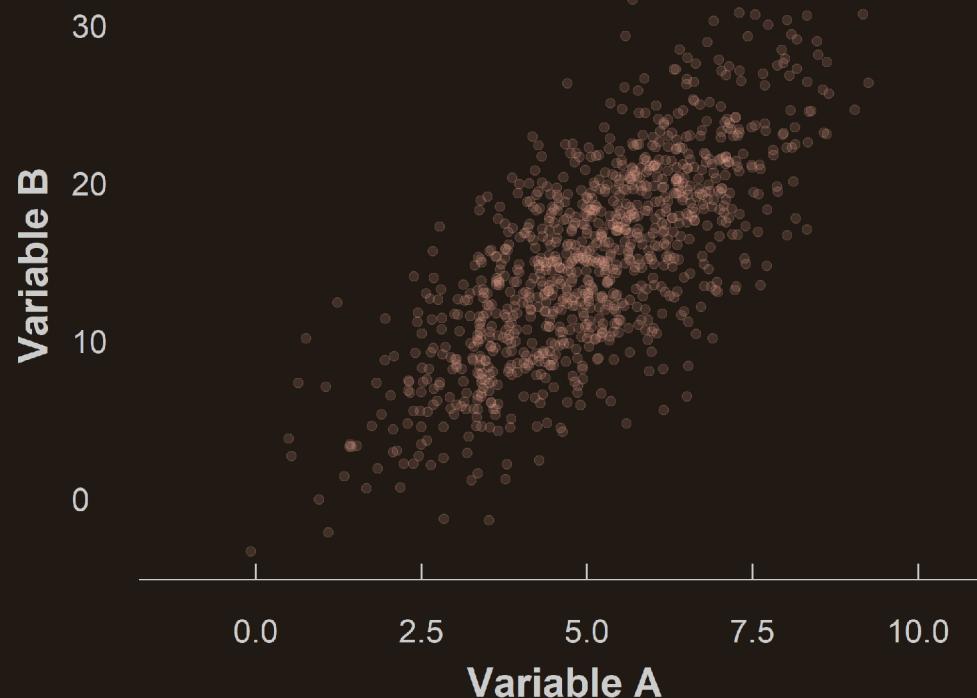
- 3.1. Binary dependent variables
- 3.2. Binary independent variables

4. Wrap up!

4. Wrap up!

1. Joint distribution

The **joint distribution** shows the possible **values** and associated **frequencies** for **two variables** simultaneously





4. Wrap up!

1. Joint distribution

→ When describing a joint distribution, we're interested in the relationship between the two variables

- The **covariance** quantifies the joint deviation of two variables from their respective mean
 - It can take values from $-\infty$ to ∞ and depends on the unit of the data

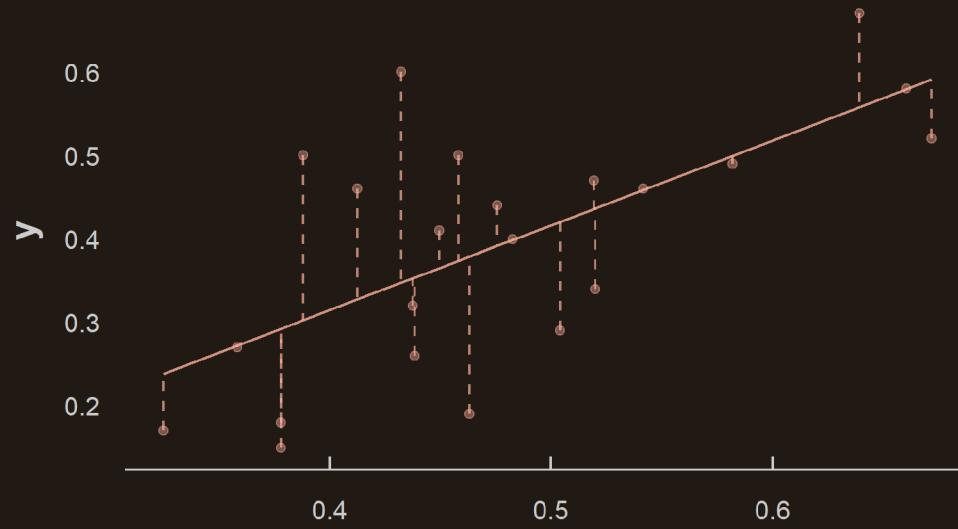
$$\text{Cov}(x, y) = \frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})$$

- The **correlation** is the covariance of two variables divided by the product of their standard deviation
 - It can take values from -1 to 1 and is independent from the unit of the data

$$\text{Corr}(x, y) = \frac{\text{Cov}(x, y)}{\text{SD}(x) \times \text{SD}(y)}$$

4. Wrap up!

2. Regression



```
## 
## Call:
## lm(formula = y ~ x, data = data)
## 
## Coefficients:
## (Intercept)          x
## -0.09129      1.01546
```

- This can be expressed with the **regression equation**:

$$y_i = \hat{\alpha} + \hat{\beta}x_i + \hat{\varepsilon}_i$$

- Where $\hat{\alpha}$ is the **intercept** and $\hat{\beta}$ the **slope** of the **line** $\hat{y}_i = \hat{\alpha} + \hat{\beta}x_i$, and $\hat{\varepsilon}_i$ the **distances** between the points and the line

$$\hat{\beta} = \frac{\text{Cov}(x_i, y_i)}{\text{Var}(x_i)}$$

$$\hat{\alpha} = \bar{y} - \hat{\beta} \times \bar{x}$$

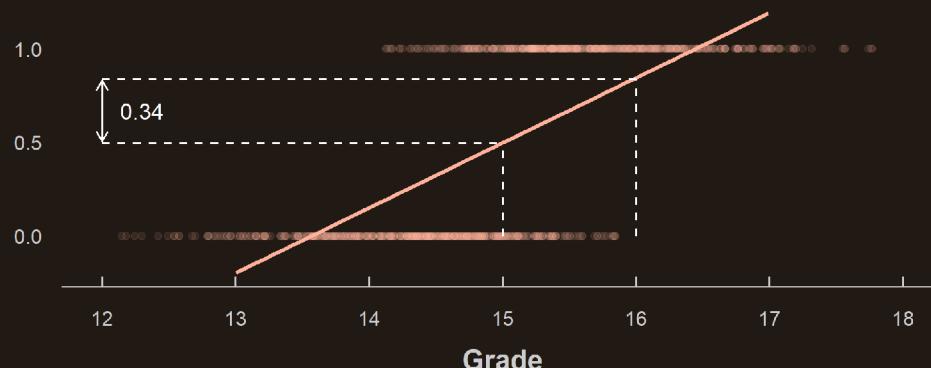
- $\hat{\alpha}$ and $\hat{\beta}$ minimize $\hat{\varepsilon}_i$

4. Wrap up!

3. Binary variables

Binary **dependent** variables

- The **fitted values** can be viewed as **probabilities**
 - $\hat{\beta}$ is the expected increase in the probability that $y = 1$ for a one unit increase in x



- We call that a **Linear Probability model**

Binary **independent** variables

- The x variable should be viewed as a **dummy 0/1**
 - $\hat{\beta}$ is the difference between the average y for the group $x = 1$ and the group $x = 0$

