Welcome

Nice to see you!

- Connect to **WiFi** with your Eduroam account or hit me up!
- **Slides and hands-on materials** are accessible on Github:

  https://github.com/Data-Science-Center-UB/Intro-Quantitative-Analysis-R

  Please download the folder `Materials` to your local machine
- You need a local **R/R Studio** installation:
  - R : https://cran.r-project.org
  - RStudio: https://www.rstudio.com/products/rstudio)

DATA SCIENCE CENTER

DataNord

University of Bremen

No Fear of Numbers

Introduction to Quantitative Data Analysis in R

CONTACT

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dsc-ub.de

2 December 2025 ▪ DSC-Training

Schedule For Today

09:00	**Welcome and Introduction**
09:30	Basic Statistical Concepts
09:50	First Steps in R: Exploring Data
11:00	Univariate Analysis
12:30	**Lunch break**
13:30	Bivariate Analysis
15:00	Multivariate Analysis
16:25	**Farewell**

Idea

We'll go through four practical parts today:

1. First Steps in R: Exploring data
2. Univariate analysis
3. Bivariate analysis
4. Multivariate analysis

→ Each part starts with a short input introducing the theory and some basic R concepts.

→ Then you'll have time to work on the exercises independently.

- **Exercise sheet (without solutions)** – for those who are already more proficient in R
- **Exercise sheet (with solutions and detailed explanations)** – for those who prefer to follow along conceptually

→ After each hands-on block, we'll go through the solutions together and discuss different approaches.

→ Don't worry if you can't finish everything — all materials remain available afterwards.

Housekeeping

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  - R : https://cran.r-project.org
  - RStudio: https://www.rstudio.com/products/rstudio)
- Please sign the attendance sheet.
- Certificates will be sent after the training.
- Questions welcome anytime ☺

Who am I?

Susanne de Vogel (she/her)

Social Scientist

- Diploma in Social Sciences (2013), University of Cologne and Utrecht University
- PhD in Sociology (2019), Martin-Luther-University Halle-Wittenberg
- Research Associate at DZHW German Centre for Higher Education Research and Science Studies (2013-2020), Hannover
- National Academics Panel Study (Nacaps) and PhD Graduate Panel; survey design, panel data analysis, research data management
- Research on educational inequalities, early career researchers, academia

Since May 2024 **Data Scientist** at the **Data Science Center**

- Training and consulting for researchers
- Data science and research data management

Brief round of introductions

- Name (pronouns)
- Institution
- Discipline
- Previous experience with quantitative data & programming software

Basic Statistical Concepts

Qualitative vs. Quantitative Research

Qualitative Research

Focus: Explores individual experiences, subjective perspectives.

Data type: Non-numerical data (e.g., words, narratives, observations).

Format: Text, audio, video.

Method: Interviews, case studies, focus groups, observations.

Analysis: Exploratory, interpretative, context-specific.

Quantitative Research

Focus: Tests hypotheses, looks for patterns and (causal) relations, makes predictions.

Data type: Numerical data (e.g., statistics, scores, ratings).

Format: Tabular data sets.

Method: Surveys, experiments, standardized tests.

Analysis: Descriptive and inferential statistics.

What is statistics?

Statistics is a branch of applied mathematics that involves

- Collection
- Description
- Interpretation
- Inference of conclusions of quantitative data

Two main types of statistics:

1. Descriptive statistics
2. Inferential statistics

Population (Grundgesamtheit)

The complete set of individuals that share common characteristics and are the **focus of a quantitative study**.

→ Group of people you are interested in.

nacaps National Academics Panel Study

Every individual who registered as a Ph.D. student at a German HEI in the 2024 academic year

German Internet Panel

Persons living in private households in Germany and aged 16-75 at the time of recruitment.

DZHW Wissenschaftsbefragung

Full-time academic and artistic staff at German universities and equivalent institutions at the time of recruitment.

FReDA The German Family Demography Panel Study

All people aged 18 to 49 living in Germany in 2020.

Sample (Stichprobe)

The specific group of individuals **chosen from the target population** to participate in the study.

→ The smaller group we actually collect data from.

→ Selected based on certain criteria or sampling methods to ensure that it **accurately represents the larger population**.

nacaps National Academics Panel Study

Full census.

German Internet Panel

Multi-stage random samples which are regionally clustered, 2012 and 2014 samples are additionally clustered in households.

DZHW Wissenschaftsbefragung

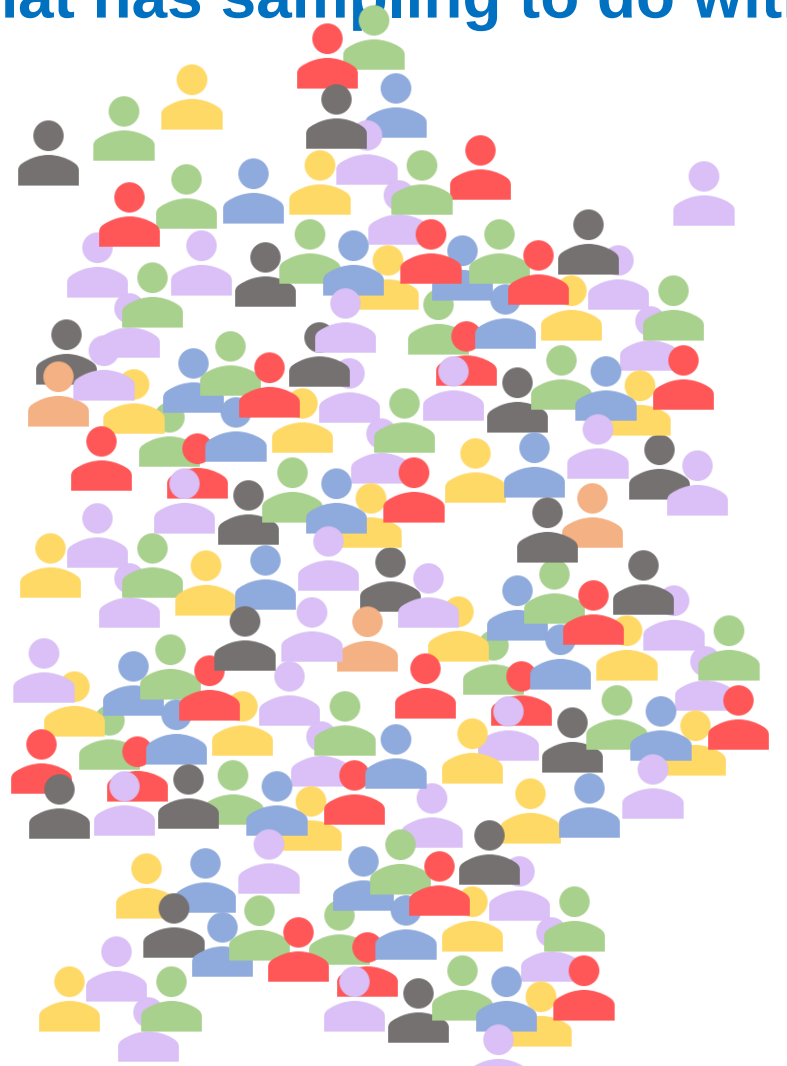
Random sample of 60,002 addresses, disproportionally stratified (with an oversampling of female professors and postdocs).

FReDA The German Family Demography Panel Study

Random two-stage sampling from the population registers of selected municipalities in Germany.

Descriptive and Inferential Statistics

What has sampling to do with statistics?



Population (N)

Sampling

Inferential Statistics

Sample (n)

Descriptive Statistics

Descriptive and Inferential Statistics

What is the difference?

Descriptive statistics

Goal: Describing the data already available (sample data).

Example:

"What is the average age of our survey participants?

"Does the average age of our participants differ by gender?

Method:

- Absolute and relative frequencies
- Central tendency (Mean, Mode, Median), Shape
- Variability (Variance, Standard Deviation)

Inferential Statistics

Goal: Make inferences (draw conclusions) from the sample and generalize them to the population.

Example:

"Do women and men differ in their average income?

"Are males more likely to gain a high salary then females?

Method:

- Hypothesis testing (Chi²-Test, t-test, ANOVA, Correlation)
- Linear- or logistic regression

What do I need to consider?

Descriptive statistics

Tell you **what your data look like**.

👉 “What is happening in my data?”

→ Works well with small samples and non-random sampling.

Inferential statistics

Tell you **whether your findings are likely a real phenomenon in your population or just coincidence**.

👉 “Is it statistically significant?”

→ Only works well with **sufficient sample size**

→ Small samples mean more uncertainty and less power to detect effects.

→ Requires **random sampling** to ensure the sample is representative of the population.

How do I know that my sample size is sufficient?

Tools and Guidelines

Australian Bureau of Statistics Sample Size Calculator

UK Sample Size Calculator

Gesis Sample Size Calculation For Complex Sampling Designs

Programmes and packages

G*Power Desktop Application

R pwr and practools packages

What is a variable?

In quantitative analysis, we investigate attributes (like characteristics) of our observations (one person, case), e.g. age, gender, income, self-efficacy score, opinions

→ Variables are the attributes we want to investigate

→ Variables can vary between people and/or over time

Example:

What does the distribution of age look like in my sample?

What does the age distribution of the population in Germany look like on 2nd December 25?

Are women more likely to reach the age of 100 in Germany than men?

Does the mean age differ between gender groups in my sample?

Which characteristics influence the age people reach in Germany?

Definition

How is each variable **measured**?

What is the **mathematical nature of the values** assigned to each variable?

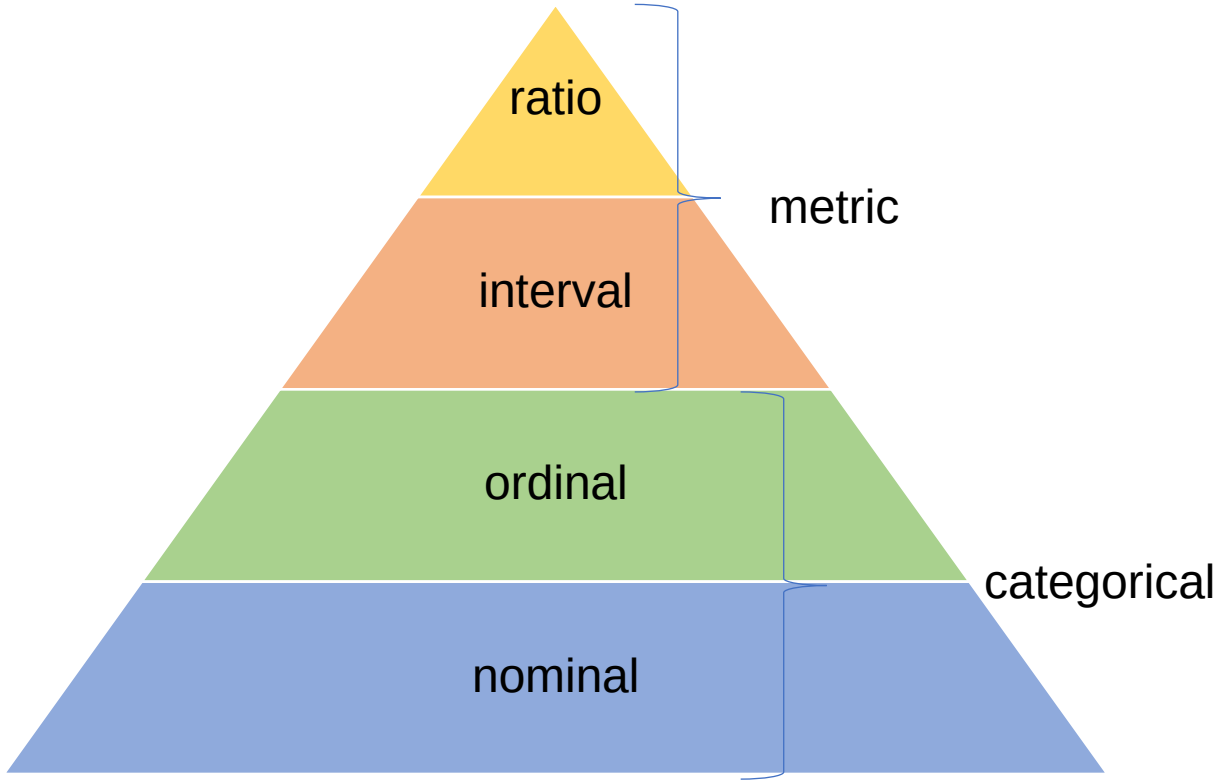
Importance

Level of measurement determines the type of **statistical analysis** you can carry out on the outcomes of your questions.

These levels reflect how data can be:

- Quantified
- Analyzed
- Interpreted

Levels of Measurement



Nominal data

Nominal data divides variables into mutually exclusive, labeled categories.

Examples

Eye color

Blue Brown Green

Smartphone

iPhone Samsung Moto

Transport

Bus Train Car

How is nominal data analyzed?

Descriptive statistics: Frequency distribution and mode

Non-parametric statistical tests

CareerFoundry. (n.d.). *Data levels of measurement: A beginner's guide*. Retrieved June 25, 2025, from https://careerfoundry.com/en/blog/data-analytics/data-levels-of-measurement/. .

Ordinal data

Ordinal data classifies variables into categories which have a natural order or rank.

Examples

School grades

Education level

Seniority level

How is ordinal data analyzed?

Descriptive statistics: Frequency distribution, mode, median, and range

Non-parametric statistical tests

CareerFoundry. (n.d.). *Data levels of measurement: A beginner's guide*. Retrieved from https://careerfoundry.com/en/blog/data-analytics/data-levels-of-measurement/ (retrieved June 25,2025.

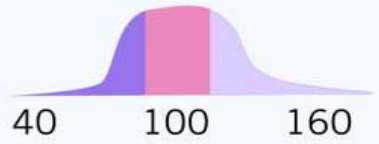
Interval data

Interval data is measured along a numerical scale that has equal intervals between adjacent values.

Examples

Temperature

IQ score



Income ranges

How is interval data analyzed?

Descriptive statistics: Frequency distribution; mode, median, and mean; range, standard deviation, and variance

Parametric statistical tests (e.g. t-test, linear regression)

CareerFoundry. (n.d.). *Data levels of measurement: A beginner's guide*. Retrieved June 25, 2025, from https://careerfoundry.com/en/blog/data-analytics/data-levels-of-measurement/.

Ratio data

Ratio data is measured along a numerical scale that has equal distances between adjacent values, and a true zero.

Examples

Weight in KG

...50 70 90...

Number of staff

...10 30 50...

Income in USD

...20k 40k 60k...

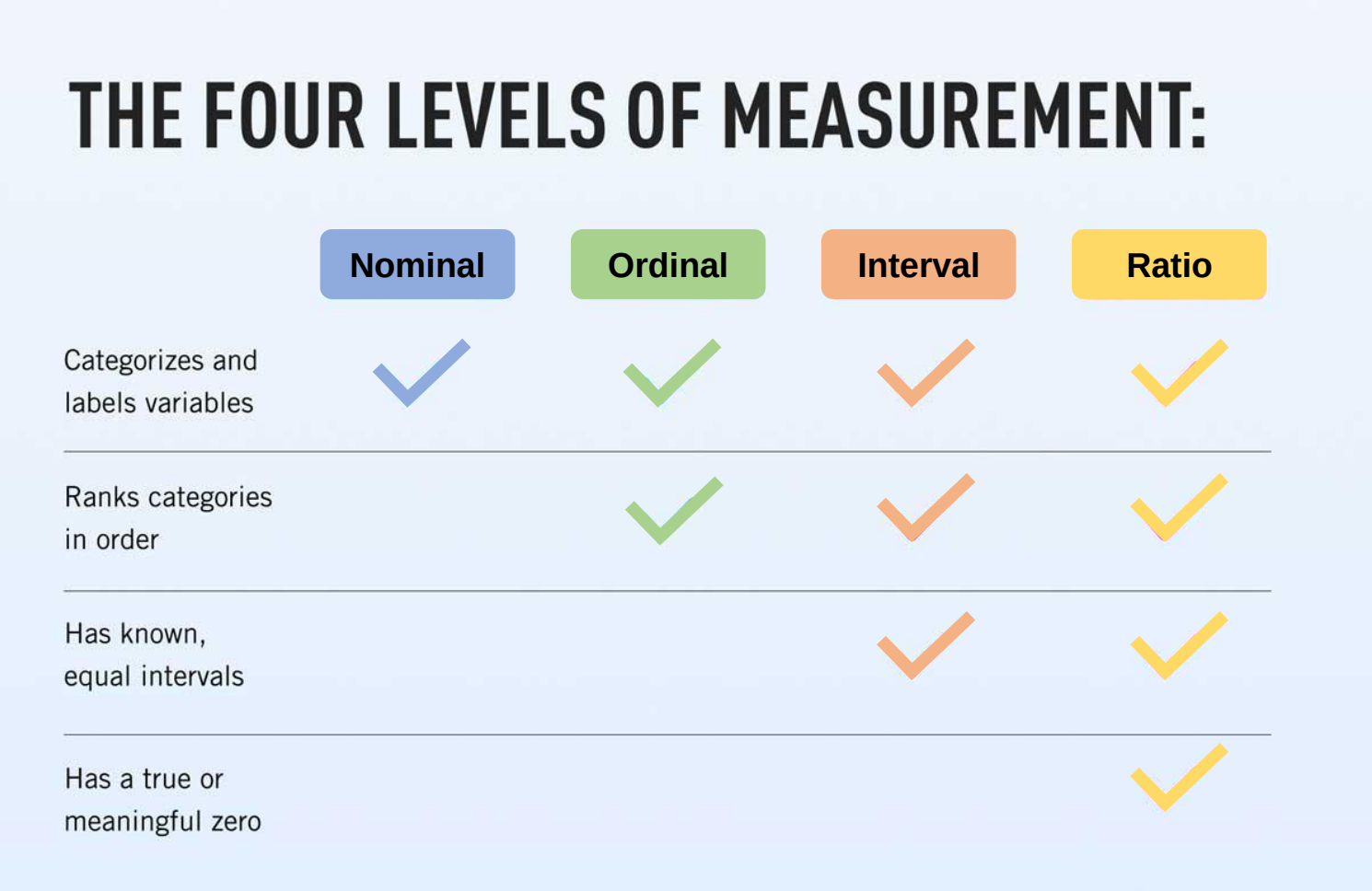
How is ratio data analyzed?

Descriptive statistics: Frequency distribution; mode, median, and mean; range, standard deviation, variance, and coefficient of variation

Parametric statistical tests (e.g. ANOVA, linear regression)

CareerFoundry. (n.d.). *Data levels of measurement: A beginner's guide*. Retrieved June 25, 2025, from https://careerfoundry.com/en/blog/data-analytics/data-levels-of-measurement/.

Comparison



CareerFoundry. (n.d.). *Data levels of measurement: A beginner's guide*. Retrieved June 25, 2025, from https://careerfoundry.com/en/blog/data-analytics/data-levels-of-measurement/.

First Steps in R

What is R?

R is a programming language designed for

- **Data manipulation** – cleaning, transforming, and preparing datasets.
- **Statistical analysis** – running summaries of your data, models and tests of your hypotheses.
- **Data visualization** – creating clear and beautiful graphs and plots.

Why do we use R?

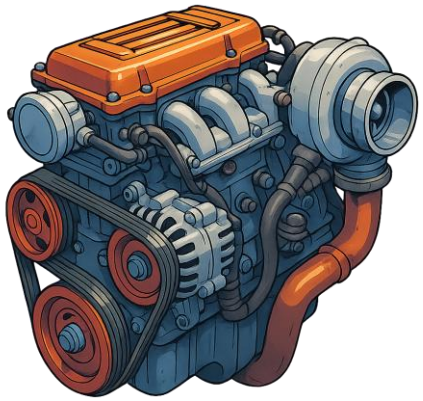
- Free and open source.
- Great for transparency and reproducibility
- Powerful and state of the art

What is the difference between R and RStudio?

R is the **programming language** itself.

→ Executes the code and does the calculations;

→ Runs in the background.



R Studio is a **development environment** (IDE) to make R easier to use.

→ Provides the graphical interface to write, run and visualize code;

→ Provides windows for code, output and plots.

You

You as a researcher use R working in R Studio.

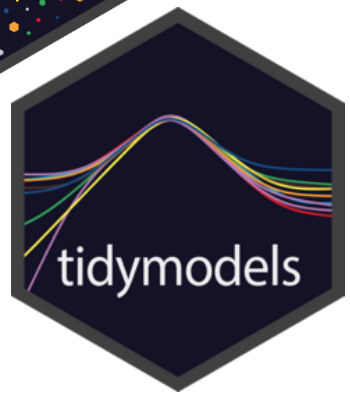
→ You have control ☺

How can I perform quantitative data analysis in R?

Base R

Core set of functions and tools that are included with R by default.

It allows you to do many data analysis tasks, but the syntax is inconsistent and can be confusing for beginners.



Tidyverse & tidymodels package

To make data work easier and more consistent, the R community has developed many **packages.**

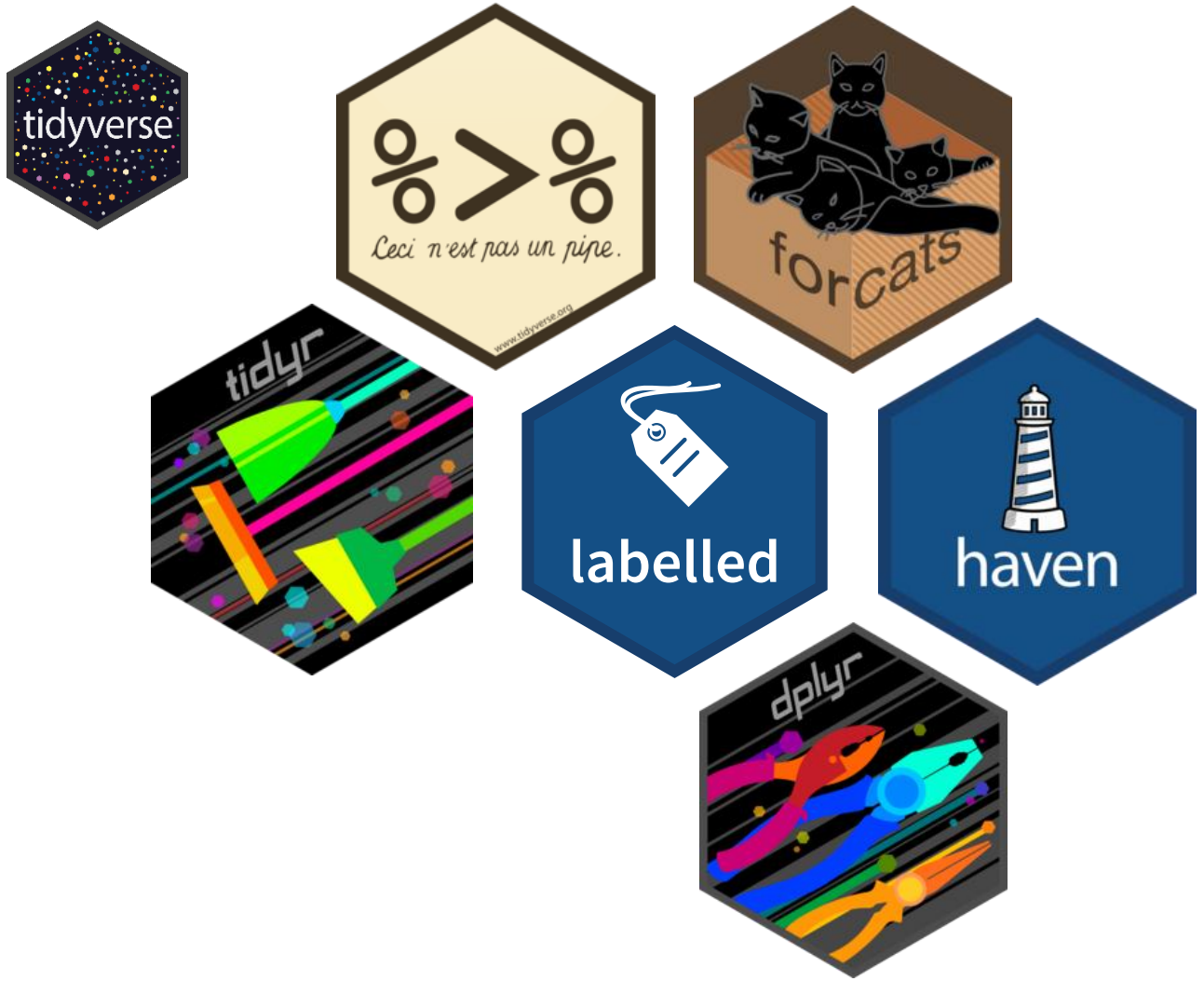
Packages are collections of functions designed to extend the capabilities of base R.

Tidyverse and tidymodels are a collection of R meta-packages designed for **data science workflows**.

- Tidyverse for data wrangling, tidying and visualization.
- Tidymodels for modeling and statistical analyses.

→ **Code has a consistent syntax and resembles natural language.**

Tidyverse and Tidymodels in R



Structure in R

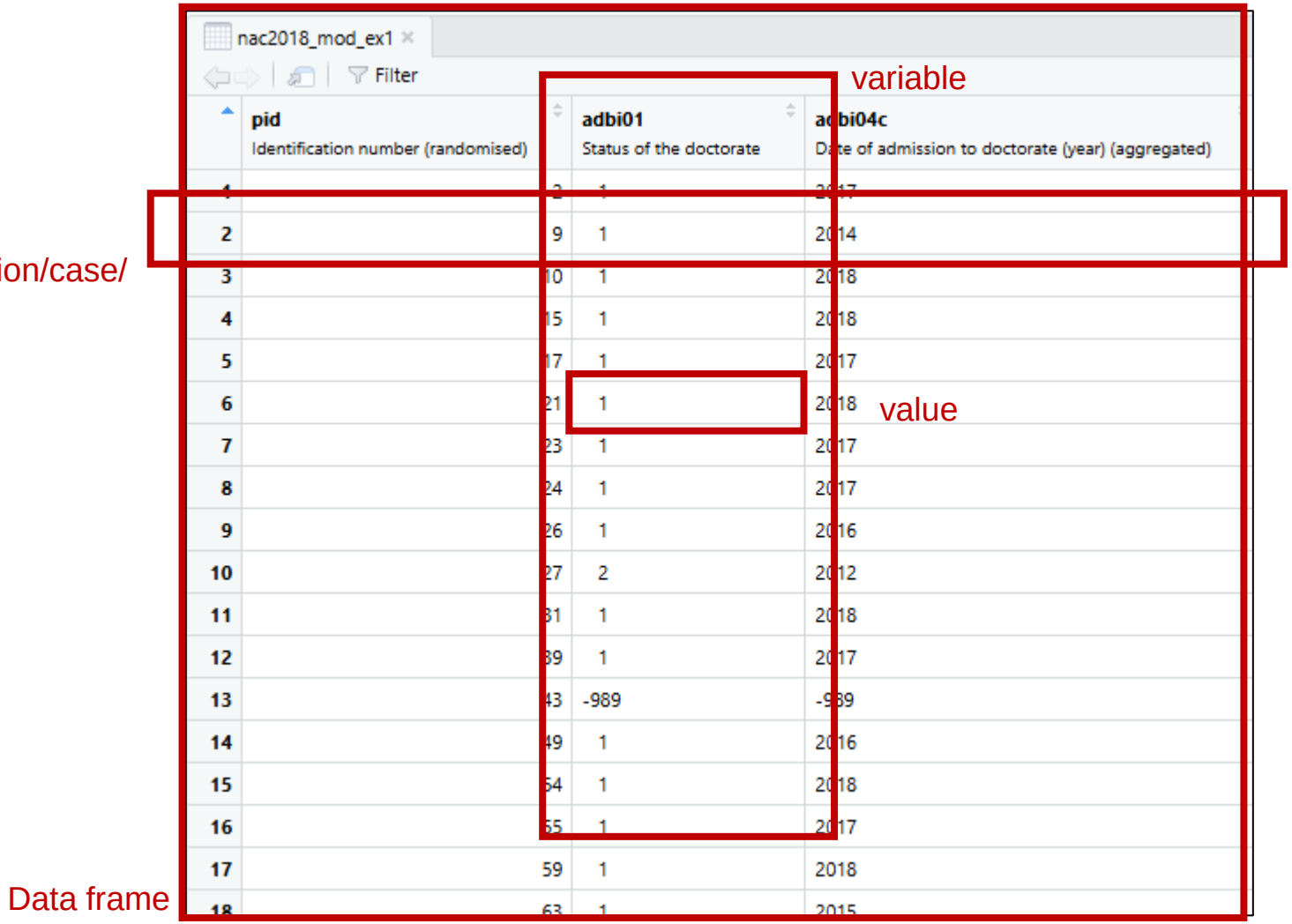
Observation/Case/Record:
One row in the dataset, usually one respondent or unit.

Variable:
One measured characteristic/attribute

Value:
The specific entry for a variable in one case (e.g., 1)

Data frame:
Dataset**,** the full table:

- rows = cases
- columns = variables
- cells = values



	pid Identification number (randomised)	adbi01 Status of the doctorate	adbi04c Date of admission to doctorate (year) (aggregated)
1		2	1	2017
2		9	1	2014
3		10	1	2018
4		15	1	2018
5		17	1	2017
6		21	1	2018
7		23	1	2017
8		24	1	2017
9		26	1	2016
10		27	2	2012
11		31	1	2018
12		39	1	2017
13		43	-989	-989
14		49	1	2016
15		54	1	2018
16		55	1	2017
17		59	1	2018
18		63	1	2015

Example: Data frame in data viewer using `View()` function

Elements of a variable

Variable name:
The short technical name used in the dataset (e.g. adem01).

Variable label:
A descriptive text for the variable (e.g. “Gender").

Value:
The specific entry for a variable in one case (e.g., 1).

Value label:
A description of what a value means (e.g., 1 = female).

Missing value:
Data not available, either left empty or coded (e.g. -996 = interview break-off).

nac2018_mod_ex1

Filter

allenging and complex tasks well	adem01 Gender	adem02a Day of birth	adem02b Month of birth
	2	11	3
	-996	-996	-996
	1	10	10
	2	15	2
	2	28	6

```
> frq(nac2018_mod_ex1$adem01)
Gender (x) <numeric>
# total N=7089 valid N=7089 mean=-157.19 sd=364.49

Value |                 Label |    N | Raw % | Valid % | Cum. %
------------------------------------------------------------------
 -998 |             no answer |    0 |  0.00 |    0.00 |   0.00
 -996 |   interview break-off | 1026 | 14.47 |   14.47 |  14.47
 -989 |              filtered |   43 |  0.61 |    0.61 |  15.08
 -969 |     unknown missing   |    0 |  0.00 |    0.00 |  15.08
 -966 |   not determinable    |   61 |  0.86 |    0.86 |  15.94
    1 |              female   | 2916 | 41.13 |   41.13 |  57.07
    2 |                male   | 3034 | 42.80 |   42.80 |  99.87
    3 |               other   |    9 |  0.13 |    0.13 | 100.00
 <NA> |               <NA>    |    0 |  0.00 |    <NA> |    <NA>
```

Example: Frequency table of variable `adem01` measuring gender using `frq()` function

Levels of Measurement & data types in R

The basic storage mode of an object in R:

Nominal, Ordinal, Interval, Ratio	`double, integer`
Strings	`character`
Binary (special variables with two categories)	`logical (TRUE/FALSE)` (booleans)

→ R often imports data as `character`, `double`, or `integer` – other variable classes need to be created explicitly e.g. for nominal (`factors`), ordinal (`ordered factors`) or date/time (`Date`) variables.

→ `Characters` usually need to be converted into another data type so that R can handle the variables correctly in analyses.

Levels of measurement & data types in R

We can use the `typeof()` function to check the data type of a variable:

```
> typeof(mydata$adem01)
[1] "double"
```

```
> typeof(mydata$adbi10a)
[1] "character"
```

Data classes in R

The class tells R how to treat an object and which methods apply.

`Factor:`	Nominal variable, internally stored as `integer` + labels.
`Ordered factor:`	Ordinal variable.
`data.frame:`	Rectangular table, `base R`‘s main data structure.
`tibble:`	Data frame in `tidyverse`.
`matrix:`	2D array (same type only).
`array:`	N-dimensional generalization of matrix (same type only).
`list:`	Generic container for mixed objects, can hold vectors, data frames, etc.

→ **Classes** = higher-level structures or behaviors **built on types.**

Data classes in R

We can use the `class()` function to check the class of an object:

```
> class(mydata4)
[1] "tbl_df"     "tbl"        "data.frame"
>
```

Dataset;

```
> class(mydata4$adbi01)
[1] "haven_labelled_spss" "haven_labelled"      "vctrs_vctr"          "double"
>
```

PhD status (ongoing, completed., etc..)
not defined as factor yet;

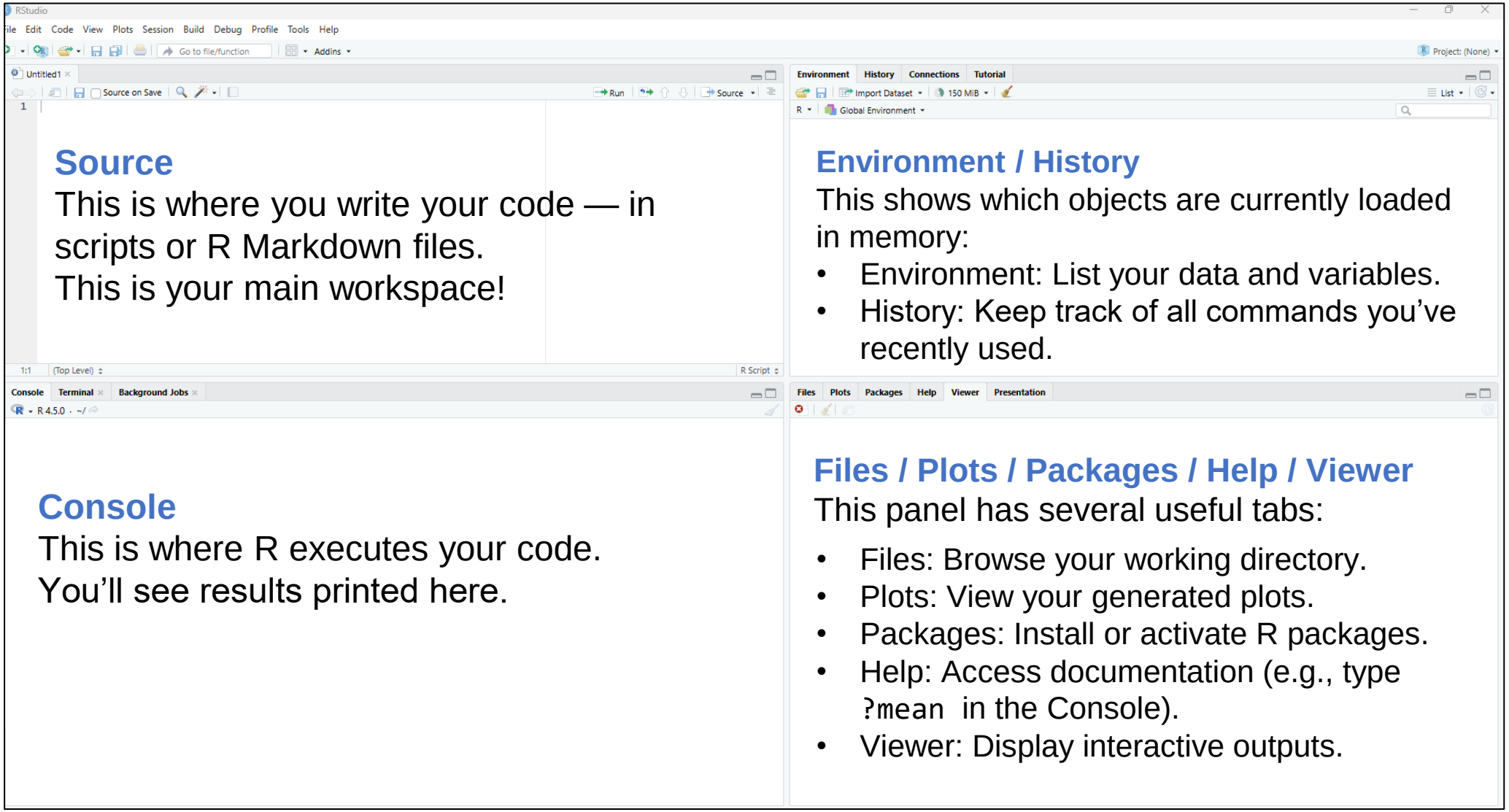
```
> class(mydata4$adem02f_g1)
[1] "ordered" "factor"

> typeof(mydata4$adem02f_g1)
[1] "integer"
>
```

Age categories
defined as factor.

RStudio layout

How does RStudio look like?



Source

This is where you write your code — in scripts or R Markdown files.
This is your main workspace!

Environment / History

This shows which objects are currently loaded in memory:

- Environment: List your data and variables.
- History: Keep track of all commands you've recently used.

Console

This is where R executes your code.
You'll see results printed here.

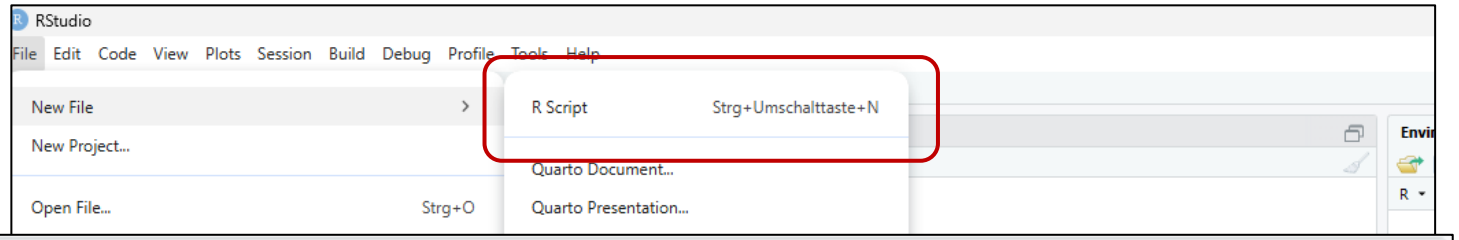
Files / Plots / Packages / Help / Viewer

This panel has several useful tabs:

- Files: Browse your working directory.
- Plots: View your generated plots.
- Packages: Install or activate R packages.
- Help: Access documentation (e.g., type `?mean` in the Console).
- Viewer: Display interactive outputs.

Initial Steps

0.1. Open Rstudio and open new script (File → New File → R script), save.



0.2. Create a header with title, author, date and description.

1. Install packages.

2. Load packages.

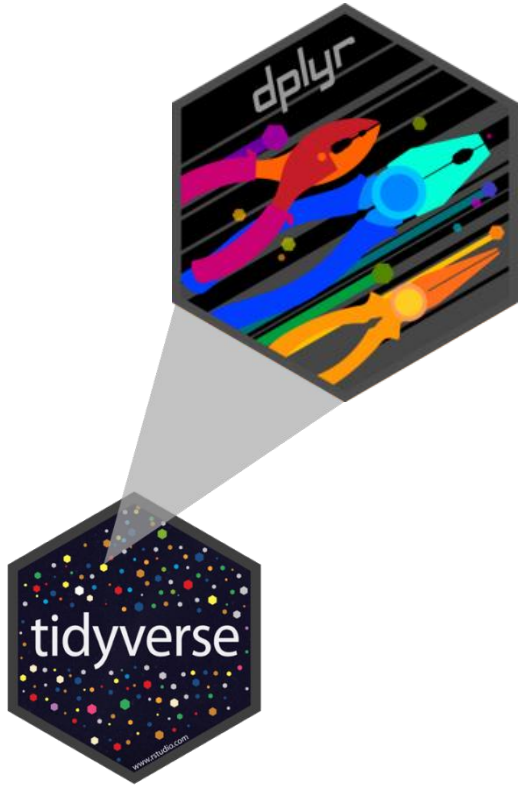
3. Set working directory.

4. Import dataset as data frame.

00_example_script.R*

Source on Save | Run | Source

```
1  # Workshop "No Fear of Numbers: Introduction to quantitative Data Analysis in R"
2  # Dr. Susanne de Vogel, Data Science Center, University of Bremen
3  # 02 December 2025
4
5  # This is an example of the necessary steps every R script starts with
6
7  # 1. Install necessary packages (only once!)
8  install.packages("tidyverse")
9  install.packages("tidymodels")
10
11 # 2. Load packages
12 library(tidyverse)
13 library(tidymodels)
14
15 # 3. Define working directory (copy path from explorer and change \ to /)
16 wd("C:/Users/Susanne/Nextcloud/share_DSC/003_Trainings/001_Workshops/2025/2025-12-02_Sdv_Data_Analysis/Materials
   /Exercises")
17
18 # 4. Load data frame
19 mydata1 <- read_sav("nac2018_workshop.sav")
20
21
```



Rules of functions

- Functions say **what to do with the data frame.**
- First argument calls the **data frame** you want to work with (and, separated with a $-sign, the **variable** you want to work with).
- Always return a **data frame.**
- **Don‘t modify** in place:
  - ➢ save as **new object,** needs to be explicitly saved.

```
```{r names}
# Check variable names in the dataset
names(mydata1)
```
```

```
 [1] "pid"     "adbi01"  "adbi10a" "adbi04c" "adbi06c" "afin04a" "afin04b" "afin04c" "afin04d" "afin04e" "afin04f"
[12] "afin04g" "afin04h" "afin04i" "afin04j" "afin04k" "alcd07"  "apsy05a" "apsy05b" "apsy05c" "adem01"  "adem02a"
[23] "adem02b" "adem02c" "adem03"  "adbi04b" "adbi06b" "adbi04a" "adbi06a"
```

```
```{r freq pid, results='hide'}
# checking frequencies of pid (output suppressed)
frq(mydata1$pid)
```
```

```
Unique identifier (x) <numeric>
# total N=7089 valid N=7089 mean=14183.45 sd=8225.83

Value | N | Raw % | Valid % | Cum. %
-------------------------------------
    2 | 1 |  0.01 |    0.01 |   0.01
```


Based on Cetinkaya-Rundel (2023). Introduction to Data Science, retrieved from https://datasciencebox.org

Running code

Run one line of code:

1. Place the cursor on the line you want to run.
2. Press **Ctrl + Enter (Windows/Linux)** or **Cmd + Enter (Mac)** or click **“Run”** at the top of your script editor.

Run several lines:

1. Highlight the lines you want to run.
2. Press **Ctrl/Cmd + Enter** again or click “**Run**” at the top of your script editor.

Run the whole script**:**

1. Click **“Source”** at the top of the script editor.
2. Or press **Ctrl + Shift + Enter.**

See the results:

The output appears in the **Console** or in the **Environment pane.**

→ For example, after mydata <- read_sav("data.sav"), you’ll see mydata listed in your Environment.

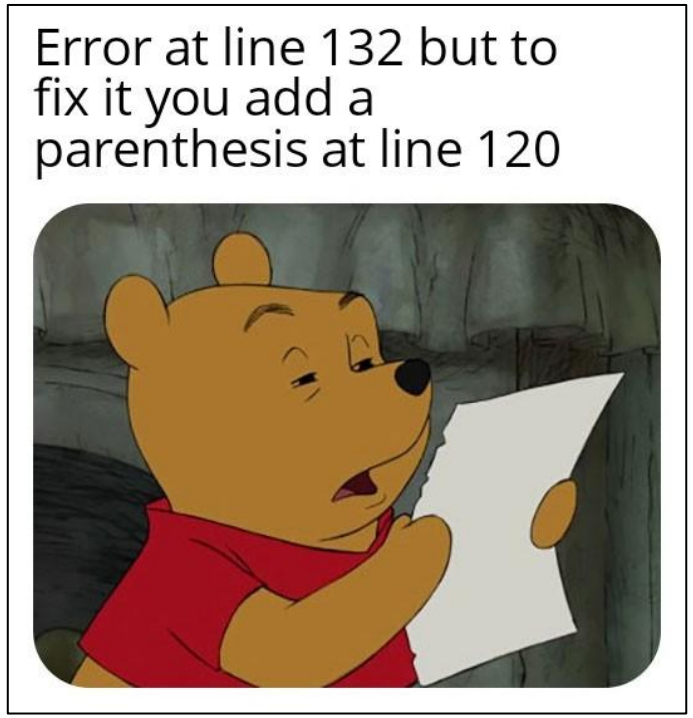
Running code: Troubleshooting

What to do if nothing happens?

→ Check that you're typing in the Script Editor or Console, not somewhere else.

What to do if there is an error message?

- Misspellings, typos, too many/too few brackets, wrong quotation marks.
- R is case-sensitive.
- Make sure you run your code in the right order (e.g., load packages before using their functions).
- You try to use an object that doesn't exist (yet).
- Wrong file path.
- Wrong data type or missing values.
- Function arguments missing or incorrect.



→ Try running the code line by line to find the issue.
→ Restart R Session (Session → Restart R) and run your code again from the beginning.

Is there a life beyond the PhD?

In this workshop, we will work with one coherent example throughout all four parts.
We focus on **two outcomes of interest**:

- **Overall life satisfaction (0-10 scale)**
- **Children (yes/no)**

We will examine how these outcomes are related to different aspects of doctoral researchers' lives and backgrounds:

PhD and Work conditions

- Status of the doctorate
- Discipline
- Emotional support during PhD
- Perceived scientific pressure
- Gross income

Attitudes and Well-Being

- Satisfaction with work-life balance
- Relationship with parents
- Self-Efficacy

Demographics

- Gender
- Age in years
- Highest vocational degree of parents
- Country of birth
- Relationship status

National Academics Panel Study (Nacaps)

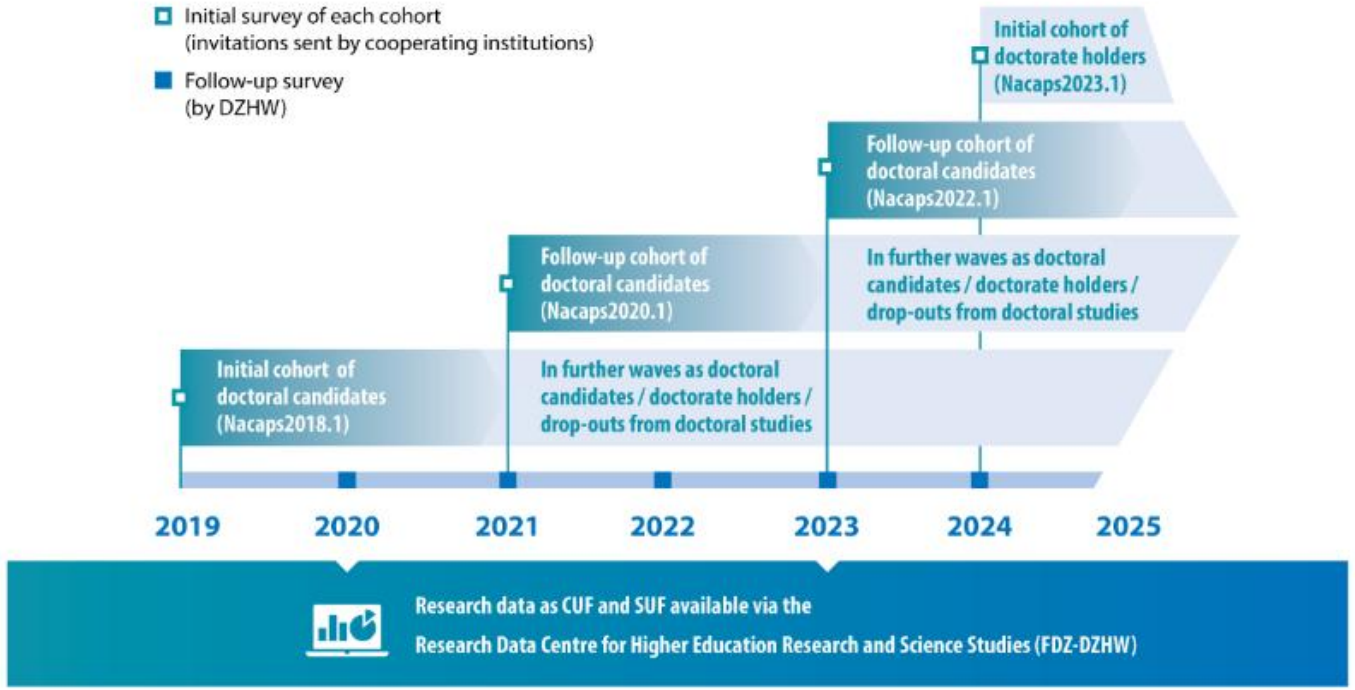
Project duration: Januar 2017 – ongoing (funded by BMBF)

Target population: full census survey

- All persons who started/completed a doctorate at a German HEI
- 66 participating universities

Survey design: multicohort longitudinal study

- Initial wave about one year after starting/graduating PhD
- Annual follow-up surveys
- New cohort every other year (doctoral candidates since 2018; doctorate holders since 2024)
- Online



Your research strategy

To explore these questions, we will:

1. start by exploring the data and getting to know our sample
2. look at univariate distributions of key variables (e.g. life satisfaction, number of children, income),
3. examine bivariate relationships (e.g. does life satisfaction differ between people of different phd status and gender)
4. finally fit multivariate models:
    - a linear regression with life satisfaction
    - a logistic regression on probability of having children

Your turn!

1. Copy folder `Materials` from to your local machine.
   → https://github.com/Data-Science-Center-UB/Intro-Quantitative-Analysis-R
   → Path to subfolder `Exercises` will be your **working directory.**
   → Folder content: data sets, exercises without & with solution

2. Do exercise **“01_qa_exploring_ex”.**

   Version with solution: **01_qa_exploring_ex_solution**

Univariate Statistics

Univariate Analysis

What is it?

Univariate statistics deal with the analysis of a single variable at a time.
The goal is to describe and summarize its distribution.

Why univariate analyses are important:

- **Describe your sample**, that means summarize who or what you studied, e.g., age, gender, education.
- **Check data quality,** e.g. detect missing values, outliers.
- Check the **shape of the distribution**, e.g. skewness and kurtosis as a foundation for further analyses;

  → Many parametric tests, e.g. t-test or ANOVA, assume normally distributed variables.
- Provide **clear and interpretable** tables and charts for publications.

What decisions to make?

1. 🎯 Which variables to analyze?

Depends on your **research question,** for example:

- Your outcome(s) of interest,
- Attributes that might affect outcome(s) of interest, e.g. group differences, influencing factor,
- Demographics.

2. ⚙ Which type of analysis and visualization to use?

Depends on the variable's **level of measurement.**

Level of measurement	Analysis	Visualization
min. nominal	Absolute/relative frequencies, mode	Bar chart
min. ordinal	cumulative frequencies, median, percentiles	Bar chart
Interval/ratio	Mean, confidence intervals Variability (Standard, Deviation) Shape (Skewness, Kurtosis)	Boxplot, Histogram

Absolute and relative frequencies

Absolute frequencies (n): The number of cases in each category or value.

→ *How many?*

Relative frequencies (%): The proportion or percentage of cases in each category.

→ *How much out of the total?*

Example:

Gender	Absolute frequency (n)	Relative frequency (%)
Female	250	50
Male	200	40
Diverse/Other	50	10
Total	**500**	**100**

Frequency table reporting

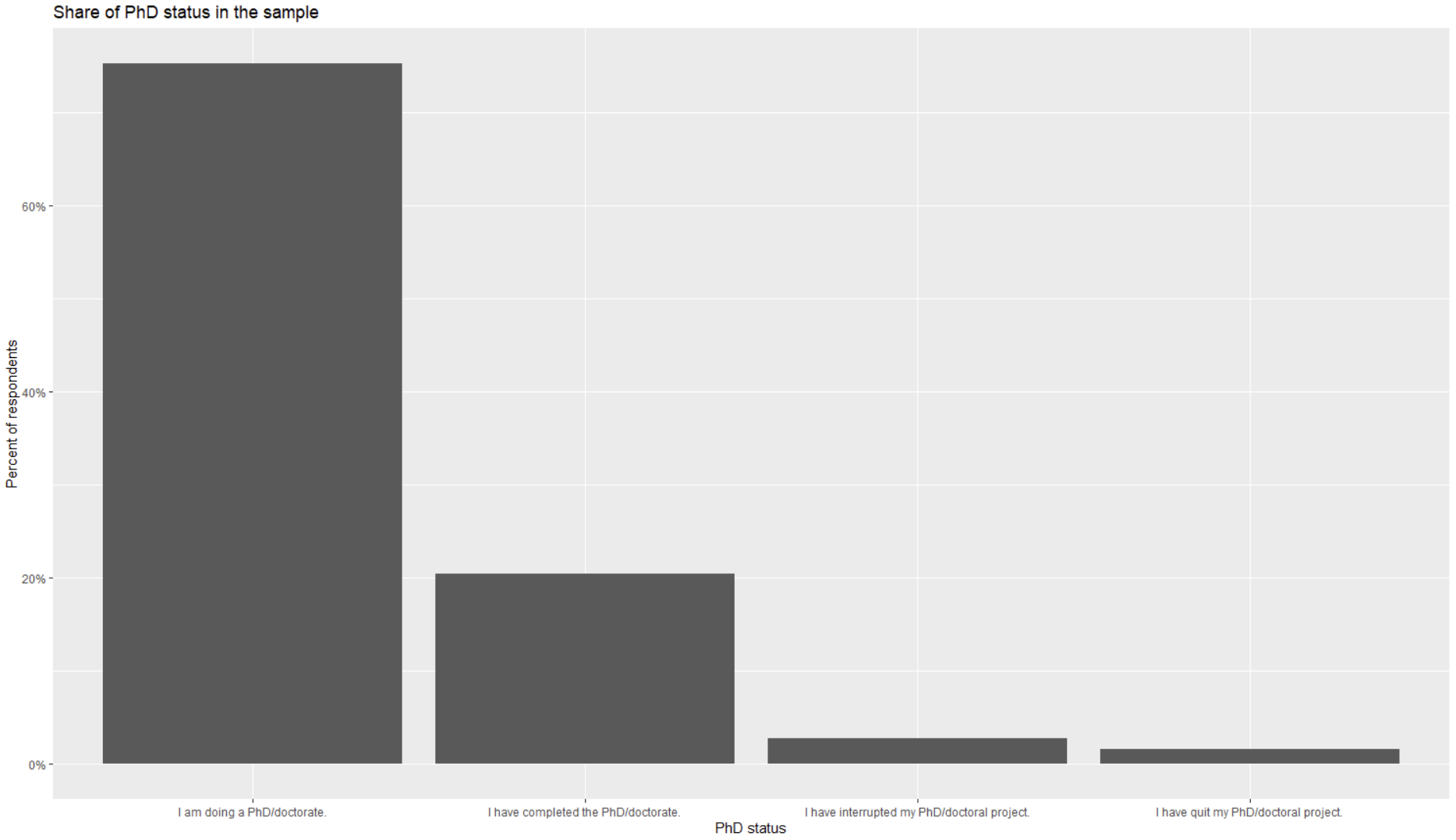
Summarize absolute and relative frequencies in frequency table:

- Absolute (n) and relative frequencies (%) in columns;
- Variable categories in row;
- Cells contain absolute numbers and percentages in each category;
- Total row at the bottom to show the total sample corresponding to 100%.

  → Categories should add up to 100% ☺

Gender	**n**	**%**
Female	250	50
Male	200	40
Diverse/Other	50	10
Total	**500**	**100**

Visualization of absolute and relative frequencies: Bar chart



Example: Bar chart of variable `bdbi01` measuring Status of the doctorate using `ggplot()`

Measure of central tendency: Mode

The mode (in German: Modus) is the most frequent value of a variable.

→ Helps to describe the most typical or common category of a variable in your sample.

Example:

Gender	Absolute frequency (n)	Relative frequency (%)
Female	250	50
Male	200	40
Diverse/Other	50	10
Total	**500**	**100**

When to use:

Works well for nominal or categorical data.

Cumulative frequencies

Cumulative frequencies: Running total of absolute or relative frequencies.

→ *How many cases fall up to including a certain category?*

→ Useful only for variables where categories have a natural order.

Example:

Highest vocational degree	Absolute frequency (n)	Relative frequency (%)	Cumulative frequency (%)
no vocational qualification	25	5	5
Apprenticeship	250	50	55
Technical/master school	50	10	65
Bachelor/master degree	150	30	95
PhD	25	5	100
Total	**500**	**100**	

65 % of respondents finished technical/master school or lower, while 35 % have an university degree.

Percentiles

Percentiles divide an ordered distribution into 100 equal parts.

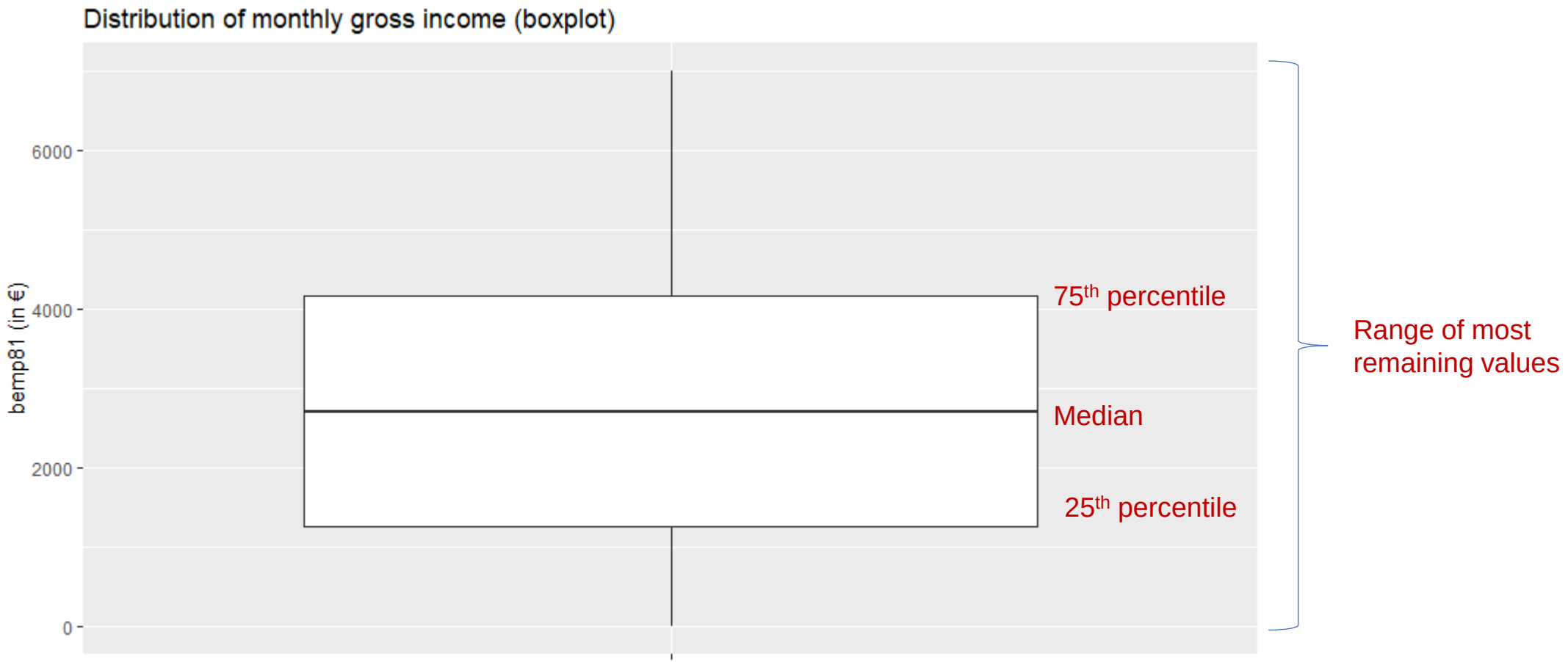
Each percentile shows the value below which a certain percentage of cases fall.

→ *How is the variable distributed?* — not just the average, but also *how spread* out it is.

→ They are based on cumulative frequencies, so they only make sense for ordinal or metric variables.

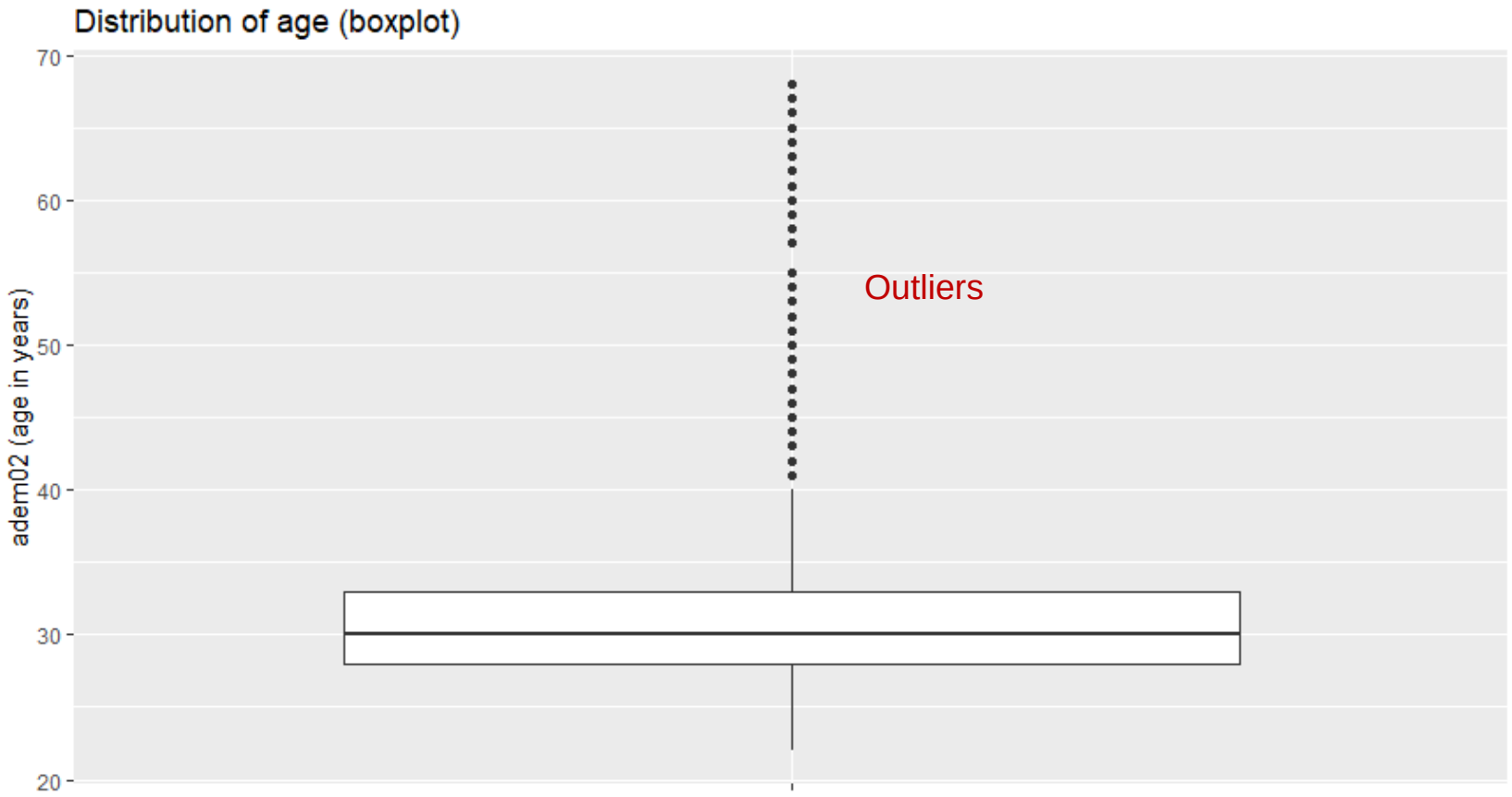
10th percentile (P10)	→ 10 % of cases are below or equal this value	quantils (because they're ¼)
25th percentile (P25)	→ 25 % of cases are below or equal to this value	
50th percentile (P50 = Median)	→ half of the data below, half above	
75th percentile (P75)	→ 75 % of cases fall below this value	
Minimum (min)	→ smallest observed value in a variable	range of possible values
Maximum (max)	→ largest observed value in a variable	

Visualization of percentiles: Boxplot



Example: Boxplot of variable `bemp81` measuring monthly gross income using `ggplot()`

Visualization of percentiles: Boxplot



Example: Boxplot of variable `adem02` measuring age in years using `ggplot()`

Measure of central tendency: Mean

The Mean (in German: arithmetisches Mittel, Mittelwert) is the arithmetic average of all values:

$$\bar{x}_{arithm} = \frac{1}{n}\sum_{i=1}^{n} x_i = \frac{x_1 + x_2 + x_3 + \cdots + x_n}{n}$$

$$\text{Mean} = \frac{\text{Sum of all values}}{\text{Number of cases}}$$

Example:

Income (€)	Absolute frequency (n)
2000	1
2200	1
2800	1
3000	1
10000	1
Total (n)	5

$$\text{Mean} = \frac{2000 + 2200 + 2800 + 3000 + 10000}{5} = 4000$$

→ Careful: The mean is sensitive to outliers.

Measures of central tendency: When to use which measure?

Measure	Works for	Sensitive to outliers?	What it tells you
Mode	Nominal, ordinal, interval, ratio	✗ No	The most frequent value
Median	Ordinal, interval, ratio	⚠ Slightly	The middle value (50% below/above)
Mean	Interval, ratio	☑ Yes	The mathematical average

Variability: Standard Deviation

Standard deviation (s or SD)

Typical deviation from the mean.

It shows, on average, **how far each value lies from the mean,** expressed in the **same unit** as the data (e.g. €)

$$S = \sqrt{\frac{\sum(x_i - \bar{x})^2}{n-1}}$$

Symbol	Meaning	Explanation
s	standard deviation	The result we want — shows how much the values vary.
x_i	each individual value	Every data point in your dataset.
$\bar{x}$	mean (average)	The “center” of all values.
x_i - $\bar{x}$	deviation from the mean	How far each value is from the mean (can be negative or positive).
$(x_i$ - $\bar{x})^2$	squared deviation	We square it so negatives don’t cancel positives.
$\sum$	“sum of”	Add up all the squared deviations.
(n - 1)	number of cases minus one	We divide by (n-1) to get an unbiased estimate for samples (→ “sample standard deviation”).
$\sqrt{\ }$	square root	Brings the result back to the same unit as the data.

Standard deviation: Interpretation

Example

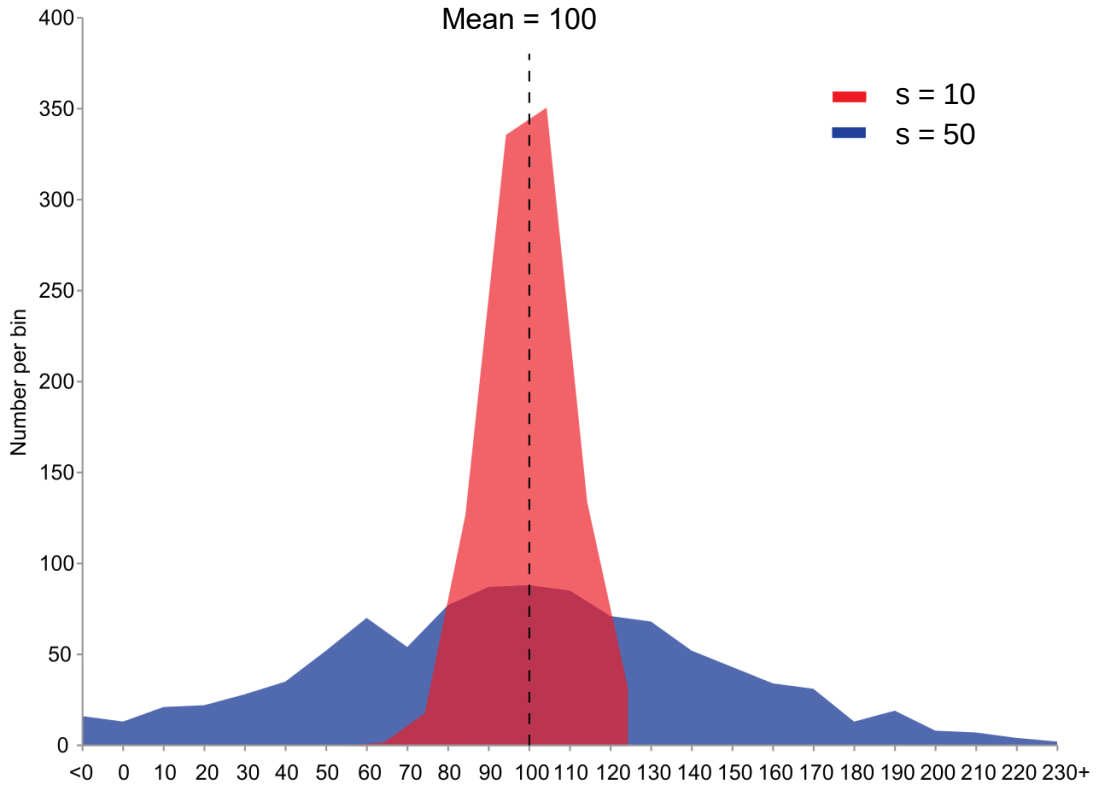
Sample of two population with the same mean but different standard deviations:

- red: small standard deviation
- blue: large standard deviation

→ Easy to interpret: “On average, values deviate from the mean by about *s* units.”

Small *s* → values are close to the mean
→ data are consistent / homogeneous

Large *s* → values are spread out widely
→ data are variable / heterogeneous



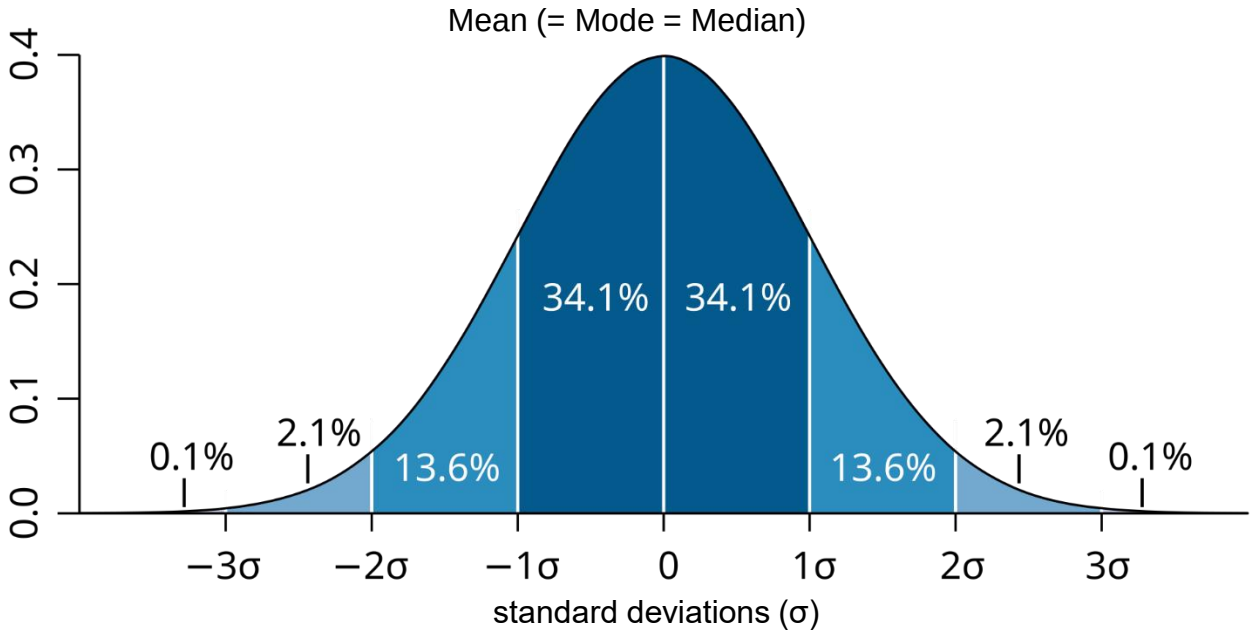
Normal distribution

The normal distribution curve (bell curve, Normalverteilung) represents how data are distributed when:

- most values are close to the mean and,
- fewer are very high or very low.

The peak in the middle marks the **mean**, which is also the **median** and **mode** in a perfect normal distribution.

- About 68% of all values lie within ±1 standard deviation of the mean.
- About 95% lie within ±2 standard deviations.
- About 99,7% cases wall within ±3 standard deviations.



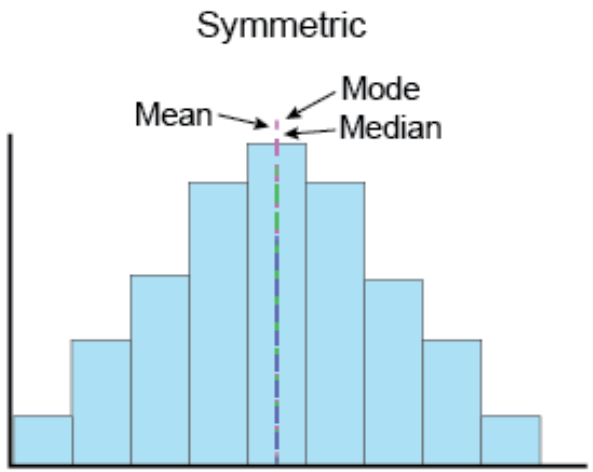
Why do I need to hear that?

Many statistical inference tests (e.g. t-tests, ANOVA) assume normality

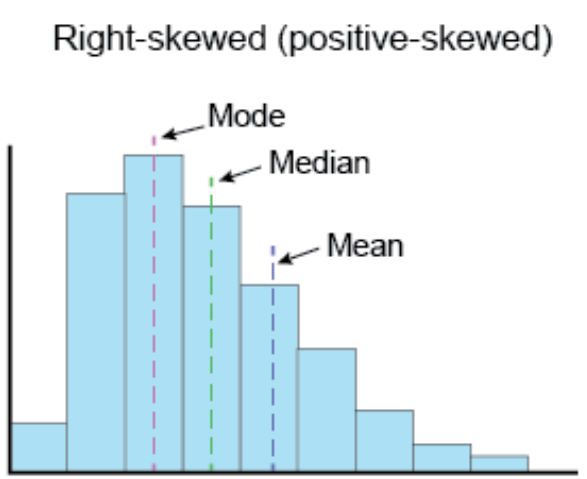
Skewness

Skewness (Schiefe) measures the asymmetry of a distribution:

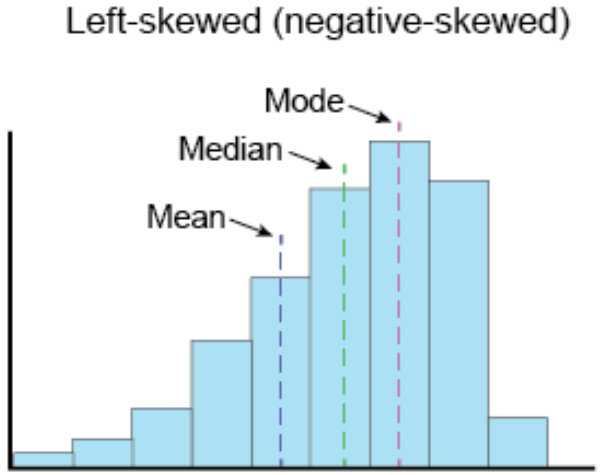
- Symmetric
- Right-skewed
- Left-skewed



Normal Distribution



Income, reaction time



Life expectancy, grades

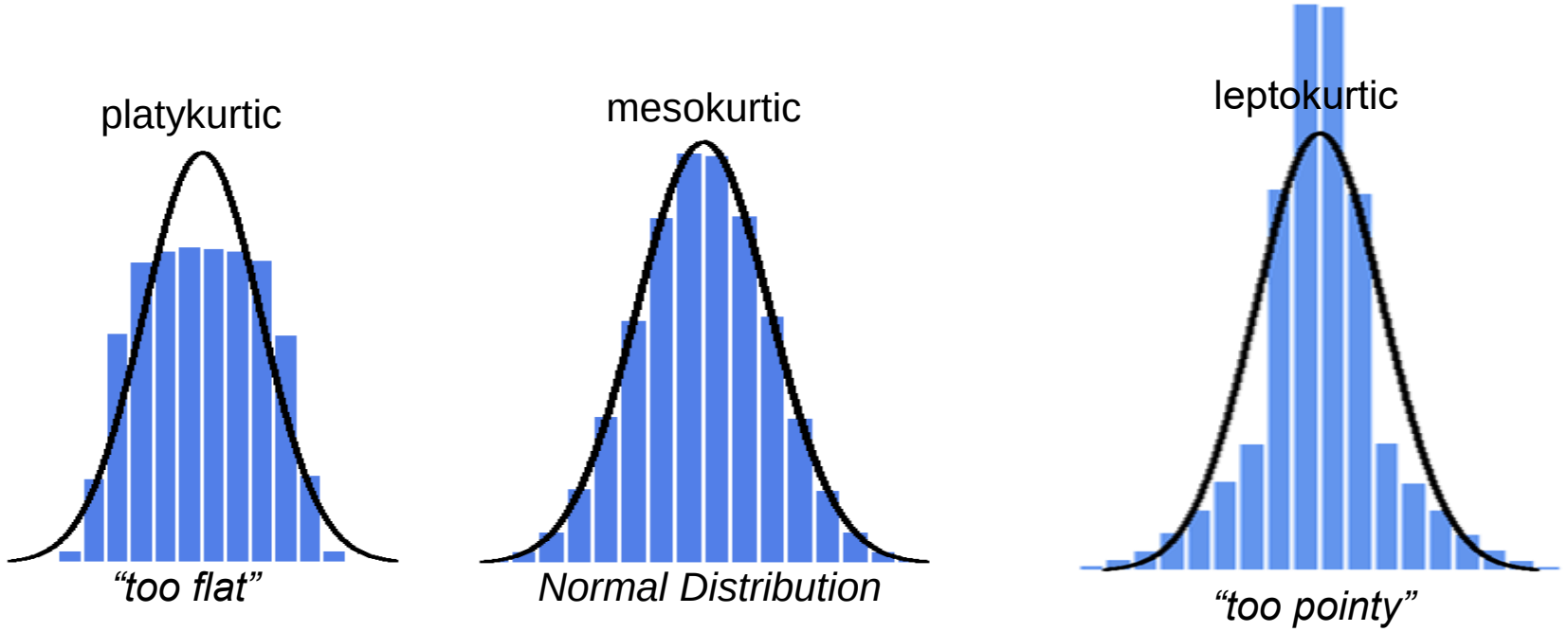
Interpretation

→ Tells you whether the values are more spread out on one side of the mean.

Skewness value	meaning
0	Symmetric, perfectly normal distribution
-0.5 – 0.5	Approximately symmetric
-1 – -0.5 and 0.5 – 1	Moderately skewed
-1 – 1	General acceptable for normal distribution
< -1 or > 1	Highly skewed

Kurtosis

Kurtosis (Wölbung) describes peakedness or flatness of a distribution compared to a normal distribution.



Interpretation

→ It describes how concentrated or spread out the values are around the mean.

kurtosis value	meaning
3.0	mesocurtic, perfectly normal distribution
< 3.0	platykurtic
> 3.0	leptokurtic

A kurtosis value between 2 to 4 (or -1 to +1 for excess kurtosis) is generally acceptable for normal distribution.

Variability: Standard Deviation and Variance

Standard deviation (s)

Typical deviation from the mean.

It shows, on average, **how far each value lies from the mean,** expressed in the **same unit** as the data (e.g. €).

→ But: negative deviations cancel each others out.

Example

values **2, 4, 6**, with a mean of **4**
Deviations from the mean:

- (2 − 4) = −2
- (4 − 4) = 0
- (6 − 4) = +2

If you simply sum them up: −2 + 0 + 2 = **0**

Variance (s^2)

Average of squared deviations from the mean.

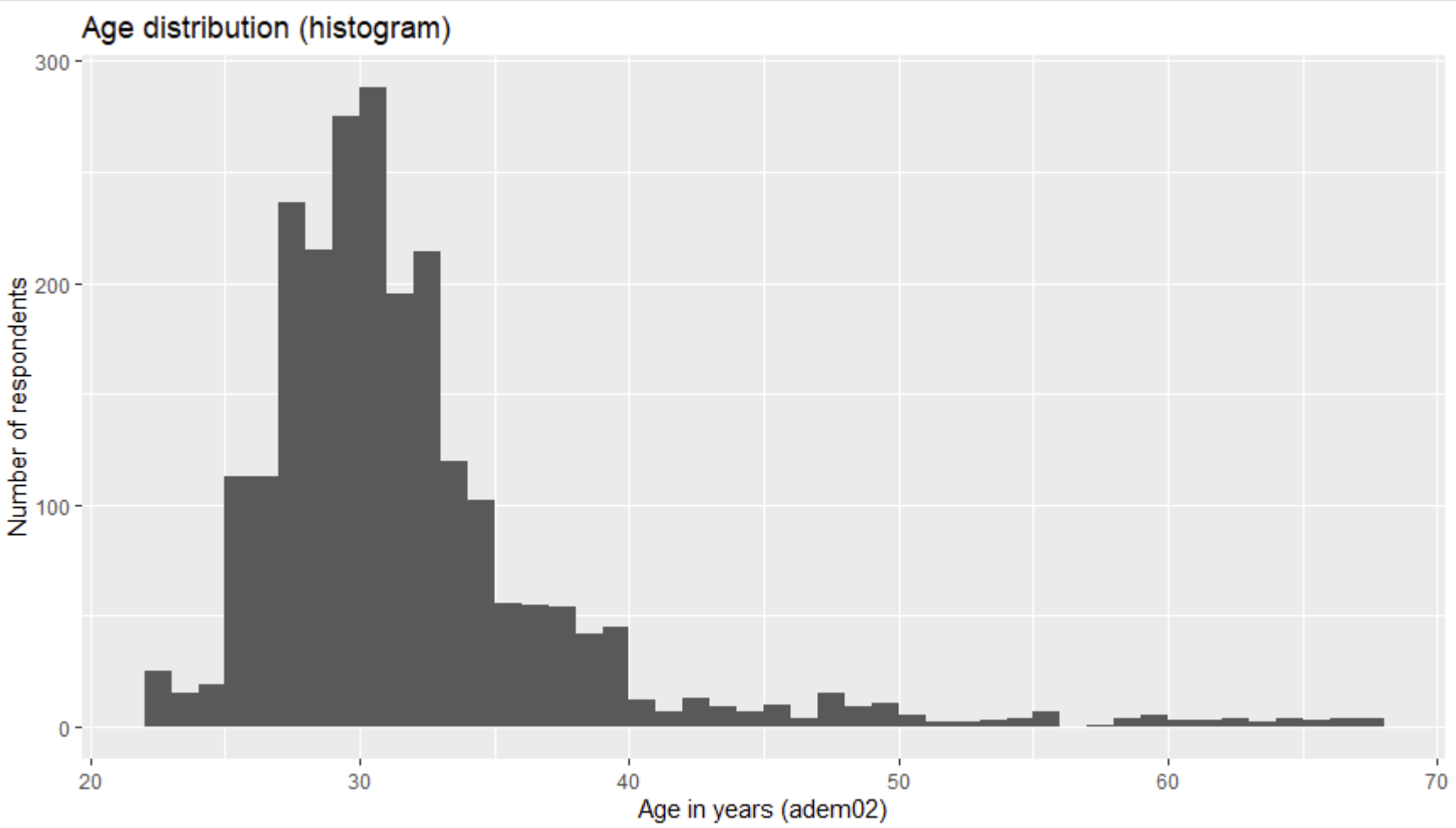
Measures how much the values differ from the mean **on average,** expressed as squared unit (e.g. €²).

$$s^2 = \frac{\sum (X - \bar{X})^2}{n-1}$$

→ Squaring prevents negative deviations from cancelling each other out.

→ Even if it's not easy to interpret directly (because of squared units), it gives us a **precise measure of overall variability** in a dataset.

Visualization: Histogram



Example: Histogram of variable `adem02` measuring age in years using `ggplot()`

Inference Statistics: Standard Error of the Mean ($SE_{\bar{x}}$)

How precise is our sample mean as an estimate of the population mean?
→ Smaller $SE_{\bar{x}}$ → more precise estimate

$$SE_{\bar{x}} = \frac{SD}{\sqrt{n}}$$

- If **SD is large** → SE is large (more variability → less precision).
- If **n is large** → SE is small (more data → more precision).

Standard deviation (SD, s)

Standard deviation describes how much individual values vary around the mean.

→ Spread of the data.

Standard Error (SE)

If we repeated the study many times, the sample means would vary. The standard error describes this variation.

→ Uncertainty of the estimate.

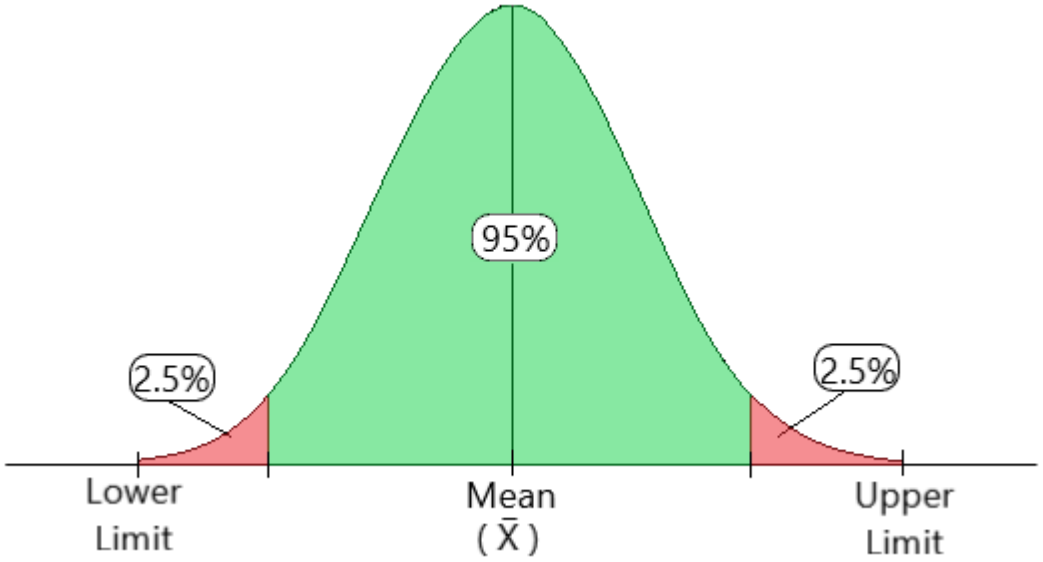
Inference Statistics: Confidence Interval (CI)

Instead of a single estimate, what is a plausible range of values for the population mean?
→ Narrow CI → more precise estimate

For a 95% CI of the mean:

$\bar{x} \pm 1.96 * SE_{\bar{x}}$

(or using a t-value for smaller samples from the t-distribution table)



Larger **SE** → **wider** CI.

Larger **n** → smaller SE → **narrower** CI.

There is no absolute rule for when a CI is ‘narrow’ or ‘wide’.
It always has to be judged relative to the measurement scale and the research question.

How to report SD and CI?

🧾 **Report always both, the mean and SD (standard deviation).**

- Standard deviation is preferred over variance because it's easier to interpret
- Variance (s^2) is usually only reported when it's directly needed for another calculation or method (e.g., ANOVA).

↔️ Whenever the mean is an important result, **report it together with the SD and a 95% confidence interval** to show how precise the estimate is.

- Standard error (SE) is mainly a technical quantity used to construct the CI and is rarely reported on its own.

Example: *M = 13.2 (SD = 0.8, 95% CI [13.04, 13.36], n = 100)*

→ The average wage/hour is 13,30 €. On average, values differ from the mean by 0,80 €.
→ A 95% confidence interval for the population mean ranges from about 13.0 € to 13.4- €.

Your turn!

1. Copy folder `Materials` from to your local machine

   → https://github.com/Data-Science-Center-UB/Intro-Quantitative-Analysis-R

   → Path do subfolder `Exercises` will be your **working directory**

   → Folder content: data sets, exercises without & with solution

2. Do exercise **“02_qa_uni_ex”**

   Version with solution: **02_qa_uni_ex_solution**

Bivariate Statistics

Bivariate Analysis

What is it?

Bivariate statistics deal with the analysis of the relationship between two variables at a time.

Why bivariate analyses are important:

- **Explore relationships**, how one variable changes with another (e.g., age and income, education and job satisfaction).
- **Compare groups,** e.g. mean differences between gender groups, income groups.
- **Check assumptions** before running multivariate models (e.g., linearity, homoscedasticity, independence).

  → Many inferential methods (e.g., regression, ANOVA, chi-square tests) **start with bivariate exploration**.
- Provide **clear and interpretable** tables and charts for publications.

What decisions to make?

1. 🎯 Which variables to analyze together?

Depends on your **research question,** for example:

- **Does one variable influence another?** e.g., education → income, age → life satisfaction
- **Are there differences between groups?** e.g., gender → mean income
- **Do two variables move together?** e.g., correlation between age and political interest
- **Is there an association between categories?** e.g., education level × employment status

2. ⚙ Which type of analysis to use?

Depends mainly on the **level of measurement**

Variable X + Variable Y	Suitable analysis	Visualization
Categorical + categorical	Cross tabulations, Chi-square test	Clustered bar chart
Categorical + metric	Mean group comparison, t-test, ANOVA	Grouped box plot
Metric + metric	Correlation, linear regression	Scatterplot

Bivariate Analysis: Categorical x Categorical

Cross tabulation (Crosstab)

A cross tabulation (or contingency table, Kreuztabelle/Kontingenztabelle) summarizes the relationship between two categorical variables by showing how often each combination of categories occurs.

→ Identifying patterns and associations between two categorical variables e.g., *Is education level related to employment status?*
→ Comparing group differences→ e.g., *Does voting preference vary by gender?*

Gender	Left	Greens	SPD	CDU/CSU	Other	Total
Women	70 *(10.8% / 50.7%)*	200 *(30.8% / 59.7%)*	180 *(27.7% / 54.5%)*	150 *(23.1% / 35.5%)*	50 *(7.7% / 40.0%)*	**650** 100%
Men	60 *(9.2% / 43.5%)*	120 *(18.5% / 35.8%)*	140 *(21.5% / 42.4%)*	260 *(40.0% / 61.6%)*	70 *(10.8% / 56.0%)*	**650**
Diverse	8 *(16.0% / 5.8%)*	15 *(30.0% / 4.5%)*	10 *(20.0% / 3.0%)*	12 *(24.0% / 2.8%)*	5 *(10.0% / 4.0%)*	**50**
Total	**138** 100%	**335**	**330**	**422**	**125**	**1,350**

Example: Voting behaviour and gender; absolute and relative frequencies absolute count (row % / column %).

Bivariate Analysis: Categorical x Categorical

Crosstab reporting

Ask yourself which variable is the grouping variable.

1. If you want to understand effects or group differences:

group = row → use row %

Example: gender differences in voting behaviour

Gender	Left	Greens	SPD	CDU/CSU	Other	Total
Women	70 *10.8%*	200 *30.8%*	180 *27.7%*	150 *23.1%*	50 *7.7%*	**650**
Men	60 *9.2%*	120 *18.5%*	140 *21.5%*	260 *40.0%*	70 *10.8%*	**650**
Diverse	8 *16.0%*	15 *30.0%*	10 *20.0%*	12 *24.0%*	5 *10.0%*	**50**
Total	**138** 100%	**335** 100%	**330** 100%	**422** 100%	**125** 100%	**1,350**

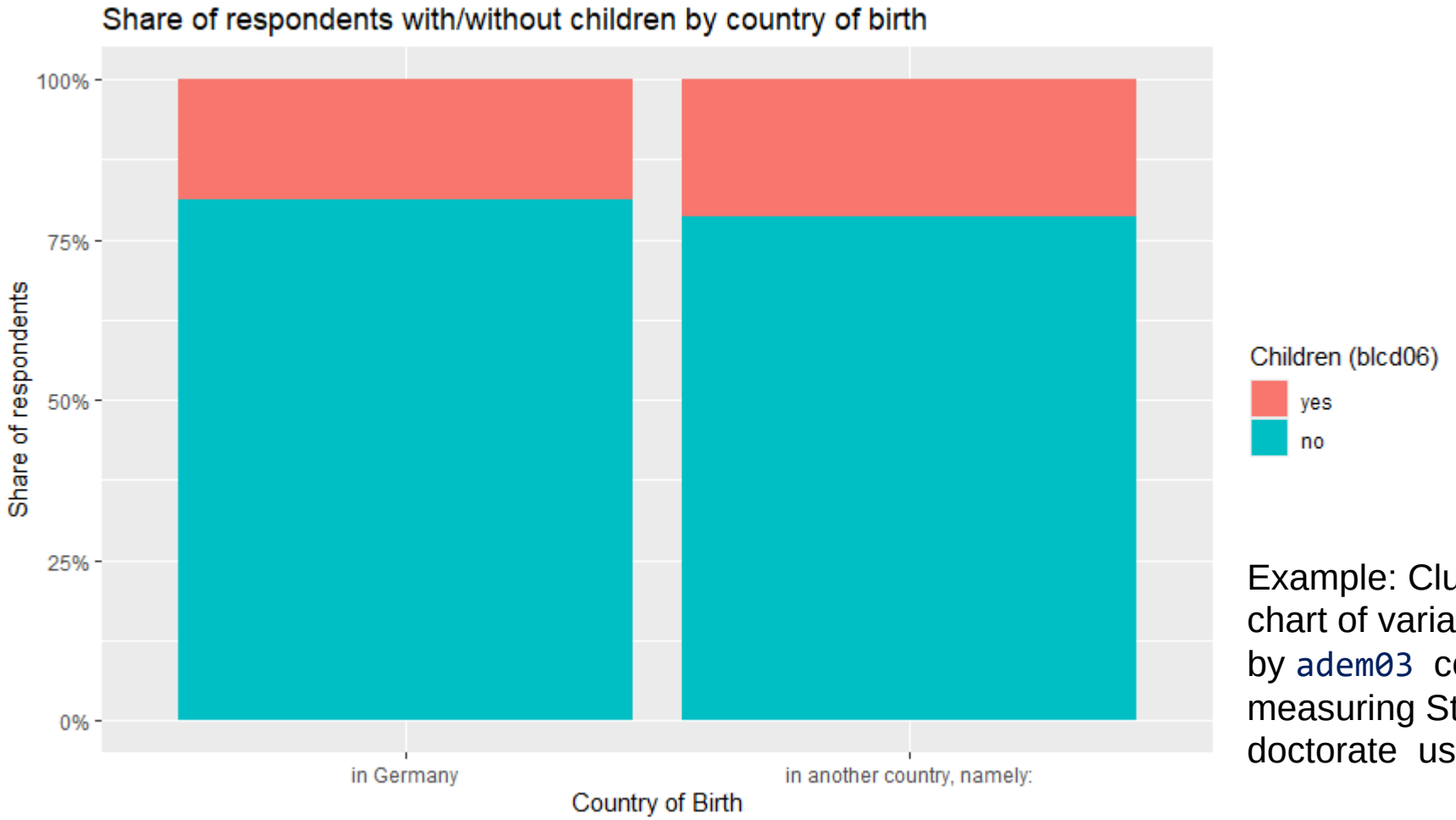
2. If you want to understand composition:

group = column → use column %

Example: gender composition of voters

Gender	Left	Greens	SPD	CDU/CSU	Other	Total
Women	70 *50.7%*	200 *59.7%*	180 *54.5%*	150 *35.5%*	50 *40.0%*	**650** 100%
Men	60 *43.5%*	120 *35.8%*	140 *42.4%*	260 *61.6%*	70 *56.0%*	**650** 100%
Diverse	8 *5.8%*	15 *4.5%*	10 *3.0%*	12 *2.8%*	5 *4.0%*	**50** 100%
Total	**138**	**335**	**330**	**422**	**125**	**1,350**

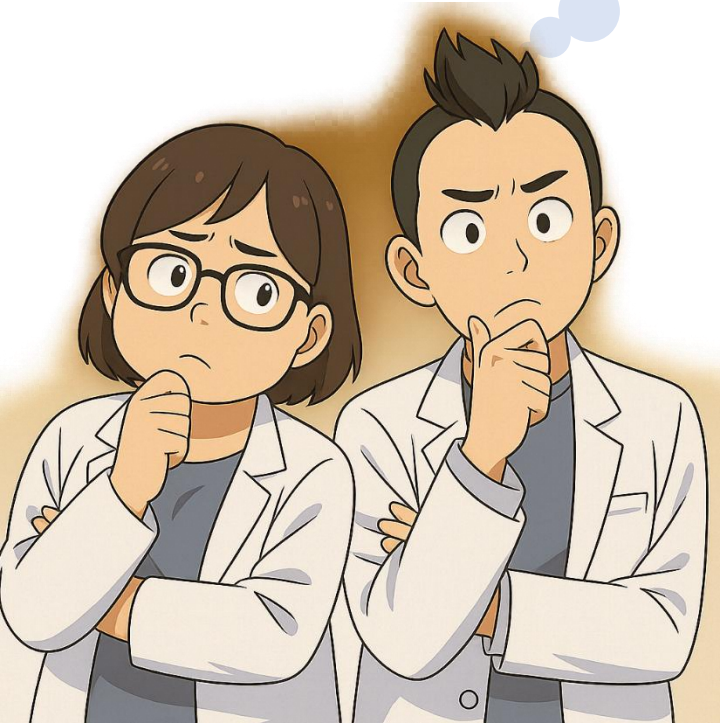
Crosstab Visualization: Clustered bar chart



Example: Clustered Bar chart of variable `blcd06` by `adem03` country of birth measuring Status of the doctorate using `ggplot()`

Inference Statistics: Hypothesis testing

How can I know that the pattern in my crosstab is real and not just coincidence?



Alternative hypothesis (H_1)

There is a relationship between the two variables.
(The differences are not random.)

Null hypothesis (H_0)

There is no relationship between the two variables.
(Any differences in the table are just random.)

Chi-square test (χ^2-test) of independence

The Chi-square test (χ^2 test) tests for statistical significance in cross tabulations.

→ The Chi-square test tells us whether we should **reject H_0**

What does the Chi-square test do? (in very simple words)

- The table shows the **observed counts** (the real data).
- The test calculates what the counts **would look like if there were no relationship** between the variables (expected counts).
- Then it compares the two.

→ The bigger the difference between observed and expected χ^2, the more likely it is that the relationship is real.

Assumptions

The chi-square test requires:

- Sufficient sample size (at least **20–30** total cases in the table).
- Expected frequency in each cell ≥ **5** (rule of thumb).
  → Otherwise collapse categories.
- Independent observations.
- Categories must be **mutually exclusive.**

Chi-square test: p-value

The p-value tells you how likely it is to see your result just by chance if there is no real effect.

$p < 0.05$ means: There is less than a 5% chance that the pattern in your data is just random.

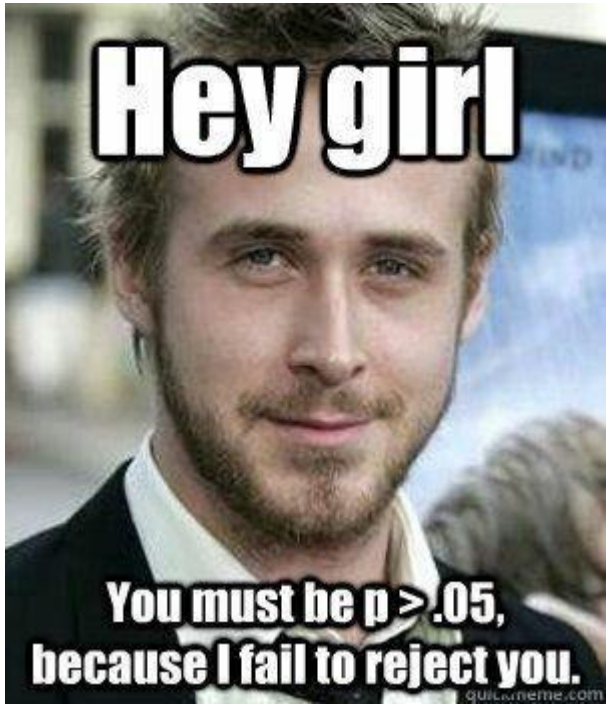
Small p-value **(< .05)** → very unlikely to be random

→ We reject H_0, there is a significant relationship.

Large p-value **(> .05)** → easily could be random

→ No significant relationship

Degrees of freedom (df) show how many independent pieces of information are available for estimating variability.
→ They adjust the test so that p-values are accurate.



Example sentence for reporting:

The association between gender and voting preference was significant, $\chi^2(8) = 21.5$, $p = .006$.

Bivariate Analysis: Categorical x Metric

Chi-square test in R

```
> tab_counts <- mydata2 %>% # store results in new data frame tab_counts
+     filter(!is.na(adem03), !is.na(blcd06)) %>% # include only cases without NA
+     tabyl(adem03, blcd06) # basic cross tabulation (absolute values)
>
> tab_counts
                      adem03 yes   no
                   in Germany 348 1503
 in another country, namely:  74  270
> chisq.test(tab_counts)

        Pearson's Chi-squared test with Yates' continuity correction

data:  tab_counts
X-squared = 1.2039, df = 1, p-value = 0.2726

>
```

Mean group differences

Mean group differences analyze whether the average value of a metric variable differs across groups of a categorical variable.

→ *Do education groups differ in their voter turnout?*

→ *Do gender groups differ in average income in €?*

Example: gender differences in monthly average gross income in €

Gender	Mean income (€)	SD (€)	n
Women	2,900	650	650
Men	3,200	850	650
Diverse	3,050	700	50

Mean group differences reporting

- The direction of comparison depends on your research question and changes how the result is perceived scientifically and socially:

  On average, men earn more than women. ***vs****. On average, women earn less than men.*

  → If you study group differences, choose the conceptually meaningful reference
  e.g., “men vs. women”.

  → If you study inequality, choose the dominant or advantaged group as reference
  e.g., “women earn less than men”.

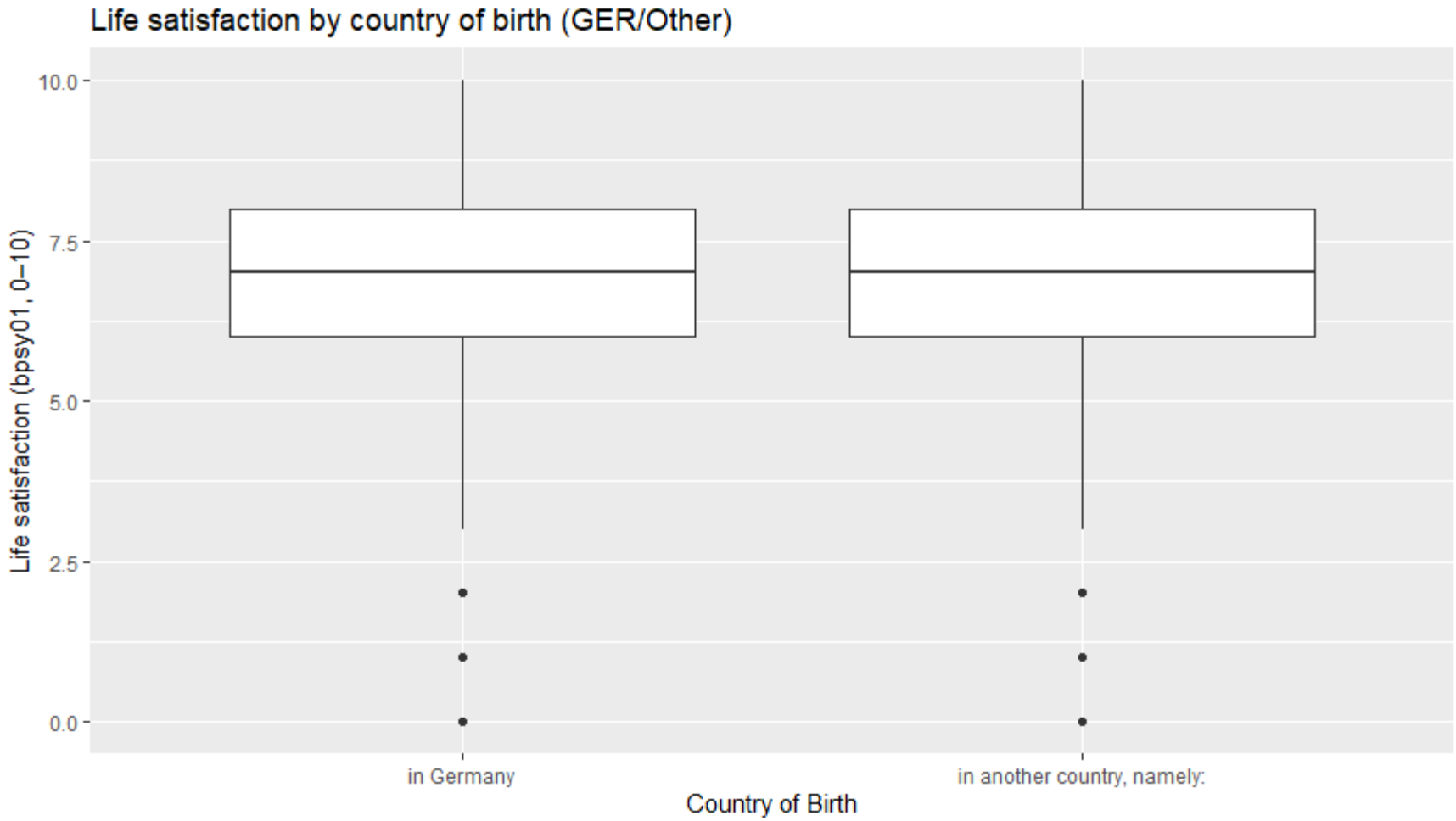
  → If you study policy impact, choose the control group as reference
  e.g., “treatment group scores higher than control”.

- State the means (M), standard deviations (SD) and group size (n) for each group.

  Women (M = 2,900, SD = 650), Men (M = 3,200, SD = 850), Diverse (M = 3,050, SD = 700, n = 50)

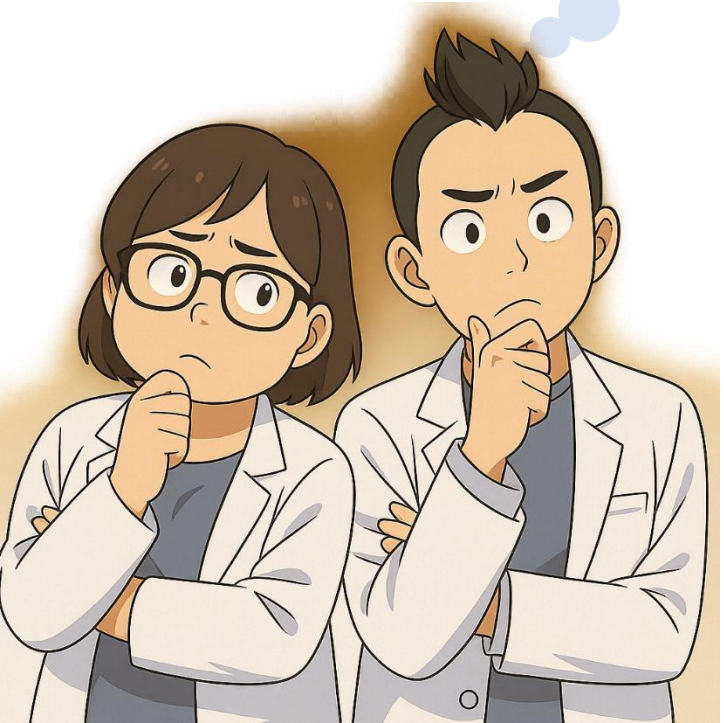
- If you want to understand how income groups are composed by gender, you need to first create income categories and then run a crosstab (income group × gender).

Mean group differences visualization: Grouped box plots



Inference Statistics: Hypothesis testing

How can I know that the differences in means between groups and not just coincidence?



Alternative hypothesis (H_1)

There is a relationship between the two variables. (The differences are not random.)

Null hypothesis (H_0)

There is no relationship between the two variables. (Any differences between groups are just random).

T-test and ANOVA

Testing for statistical significance in mean differences across groups.

T-test

Compares means of two groups

Are the two group means different beyond what we would expect by chance?

→ Looks at the **difference between the means** relative to the **variation within the groups.**

Independent t-test

Compares means of **two separate groups** that have **different participants**.

- Employed vs unemployed
- Treatment group vs. control group

Paired t-test

compares means **within the same individuals/paired units.**

- Before vs. after an intervention (same participants)
- Matched pairs (e.g., each patient matched with a control)

(oneway) ANOVA (F-test)

Compares means of three or more groups

Do at least one of these group means differ significantly?

- Male, female, diverse
- Scientific discipline

→ Looks at the **difference between the means** relative to the **variation within the groups.**

→ ANOVA only tells you that a significant difference exists, not which groups differ.

Bivariate Analysis: Categorial x Metric

T-test and ANOVA: p-value

The p-value tells you how likely it is that the difference we observe between group means is just due to random chance.

→ Test become significant if the **between-group variance is much larger than the within-group noise.**

$p < 0.05$ means: There is less than a 5% chance that the differences in group means in your data is just random.

Small p-value **(< .05)** → very unlikely to be random.

→ We reject H_0, there is a significant group difference.

Large p-value **(> .05)** → easily could be random.

→ No significant group difference.

Example sentence for reporting:

The mean voting turnout differed significantly between employed and unemployed, t(128) = 2.45, p = .016.

t-test: t(df) = value, p = …

Example sentence for reporting:

The mean income differed significantly across gender groups, F(2, 147) = 4.21, p = .017.

ANOVA: F(df1,df2) = value, p = …

Bivariate Analysis: Categorical x Metric

T-test in R

```
        Welch Two Sample t-test

data:  bpsy01 by adem03
t = 3.6655, df = 452.22, p-value = 0.0002761
alternative hypothesis: true difference in means between group in Germany and group in another country, namely: is not equal
to 0
95 percent confidence interval:
 0.2035913 0.6742183
sample estimates:
                mean in group in Germany mean in group in another country, namely:
                                7.107509                                 6.668605
```

ANOVA in R

```
> summary(anova_gender)
              Df Sum Sq Mean Sq F value Pr(>F)
adem01         1      0   0.138   0.038  0.845
Residuals   2194   7963   3.629
>
```

T-test and ANOVA: Assumptions

T-test and ANOVA require:

- Approximately normal distribution within each group.
- Homoscedasticity: equal variances, that means groups have similar spread.

  → If not, use Welch t-test or Welch ANOVA (more robust).
- No strict minimum sample size, BUT small samples = unstable results, low power, and sensitivity to non-normality.

  → T-test and ANOVA work best with:
  - At least 20-30 cases per group (independent) or pairs (paired);
  - Similar group size.

  → To detect small differences, you often need larger samples.

Pearson‘s correlation (r)

Correlation analyses examine whether two metric variables move together and if changes in one variable are systematically associated with changes in the other.

→ *Do older people report higher political interest?*
→ *Do hours studies predict exam scores?*

Example: Relationship between age in years and political interest score (0–10)

Statistic	Value
Correlation (r)	0.32
p-value	0.004
n	1,100

Pearson‘s correlation (r): Visualization

Scatterplot

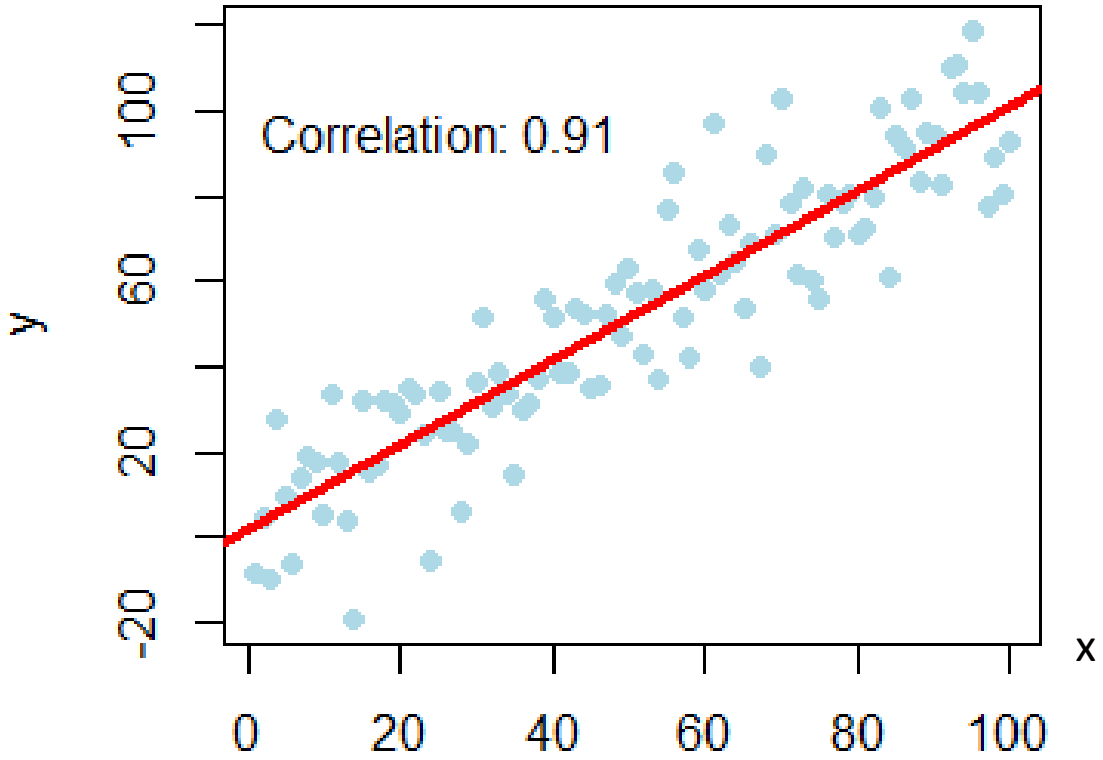
Each point represents one person/case;

X-axis = variable 1;

Y-axis = variable 2;

Shows the pattern: positive, negative, or zero;

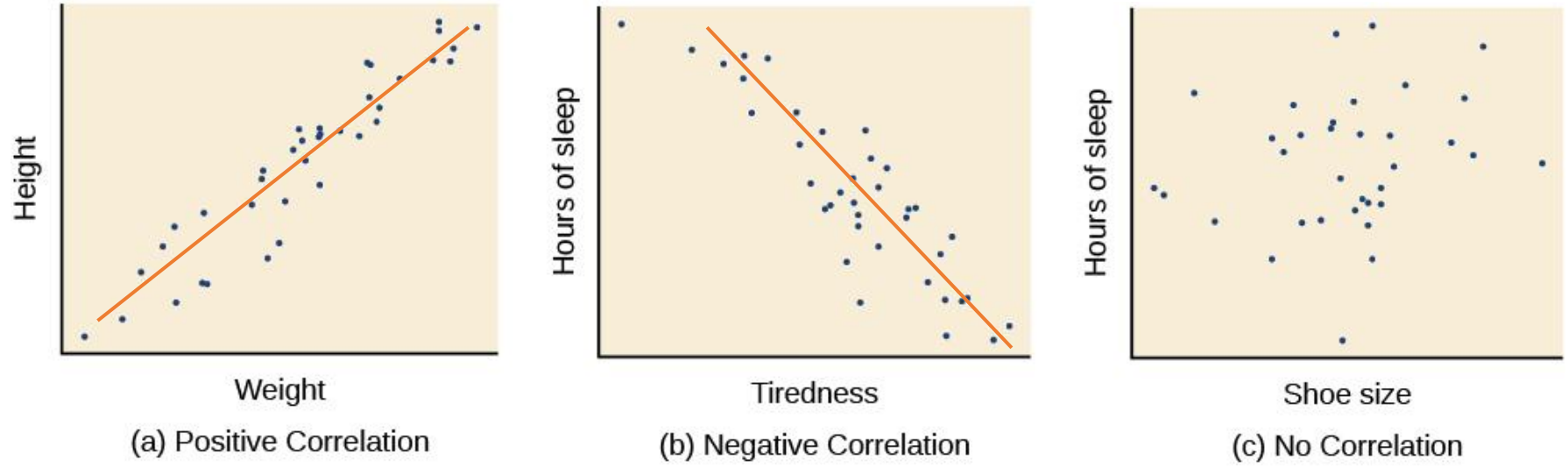
Add a regression line to show the trend.



https://r-coder.com/correlation-plot-r/

Pearson correlation (r) interpretation

r tells you whether people who have more of X also tend to have more (or less) of Y.



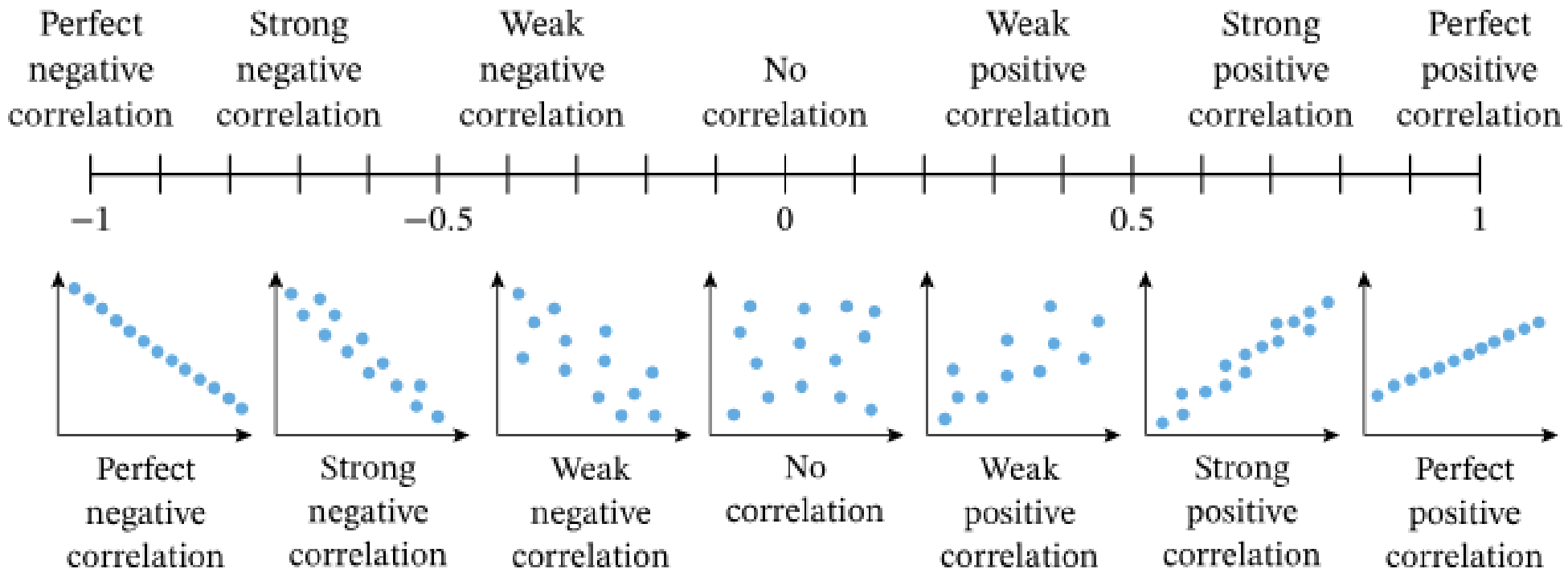
https://opened.cuny.edu/courseware/lesson/16/student/?section=2

The correlation coefficient r ranges from –1 to +1

- r > 0: when X increases, Y tends to increase (positive relationship).
- r < 0: when X increases, Y tends to decrease (negative relationship).
- r ≈ 0: no systematic relationship.

Pearson correlation (r) interpretation

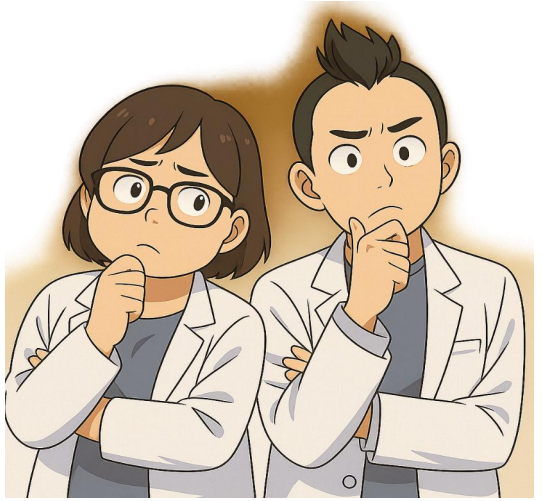
r's size gives you information about the strength of the relationship:



https://www.nagwa.com/en/explainers/143190760373/

Pearson correlation: p-value

How can I know that the relationship between the two variables are not just coincidence?



The p-value tells you how likely it is to observe a correlation as big as the one you found, if in reality there is no relationship between X and Y.

$p < 0.05$ means: There is less than a 5% chance that the correlation is just random.

Small p-value **(< .05)** → We reject H_0, there is a significant correlation.

Large p-value **(> .05)** → No significant correlation.

Example sentence for reporting:

There was a significant positive correlation between study hours and exam scores, $r(248) = .45$, $p < .001$, indicating that students who studied more tended to score higher.

Pearson's r: r(df) = value, p = …

Pearson correlation (r): Assumptions

Pearson correlation require:

- Both variables are metric;
  → Use Spearman correlation for ordinal variables.
- Linear relationship;
  → The relationship should look roughly like a straight line in a scatterplot.
- No strong outliers;
- Approximately normal distribution;
- Homoscedasticity: the spread of Y should be fairly similar across values of X;
  → Equal variance" of points along the line.
- Independent observations;
  → Each case/person must represent an independent data point.

Your turn!

1. Copy folder `Materials` from to your local machine
   → https://github.com/Data-Science-Center-UB/Intro-Quantitative-Analysis-R
   → Path do subfolder `Exercises` will be your **working directory**
   → Folder content: data sets, exercises without & with solution

2. Do exercise **“03_qa_bi_ex”**

   Version with solution: **03_qa_bi_ex_solution**

Multivariate Analyses

Correlation coefficient vs. Simple linear regression

Correlation measures tell you the strength and direction of an association.

→ It does not assume one variable predicts the other;

→ Correlation does not mean causation.

Regression models how one variable (*X*) predicts another (*Y*).

It gives you a mathematical equation ($Y = a + bX$).

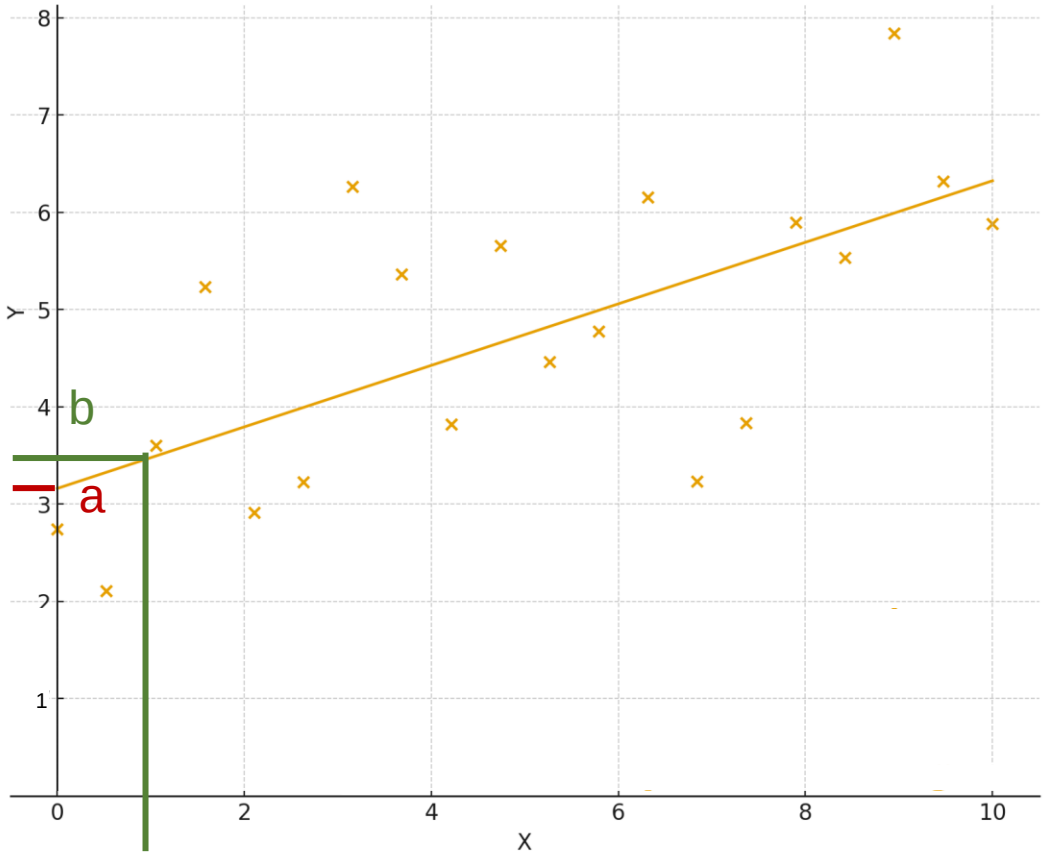
- It tells you the size of the effect (slope);
- It includes significance tests and uncertainty (SE, p-value, CI).

Linear regression models the relationship between two variables with a straight line.

Simple linear regression is the specific case of linear regression with exactly one predictor variable.

How does a simple linear regression look like?

Example: We model how study time predicts exam performance



X = *Hours of study per week*, Y = *Exam score*

(Y = a + bX).

Y = Dependent variable = exam score.

→ Variable you want to explain.

X = Predictor = hours studied.

→ Variable you assume has an effect on Y.

a = Intercept = exam score if hours studied = 0.

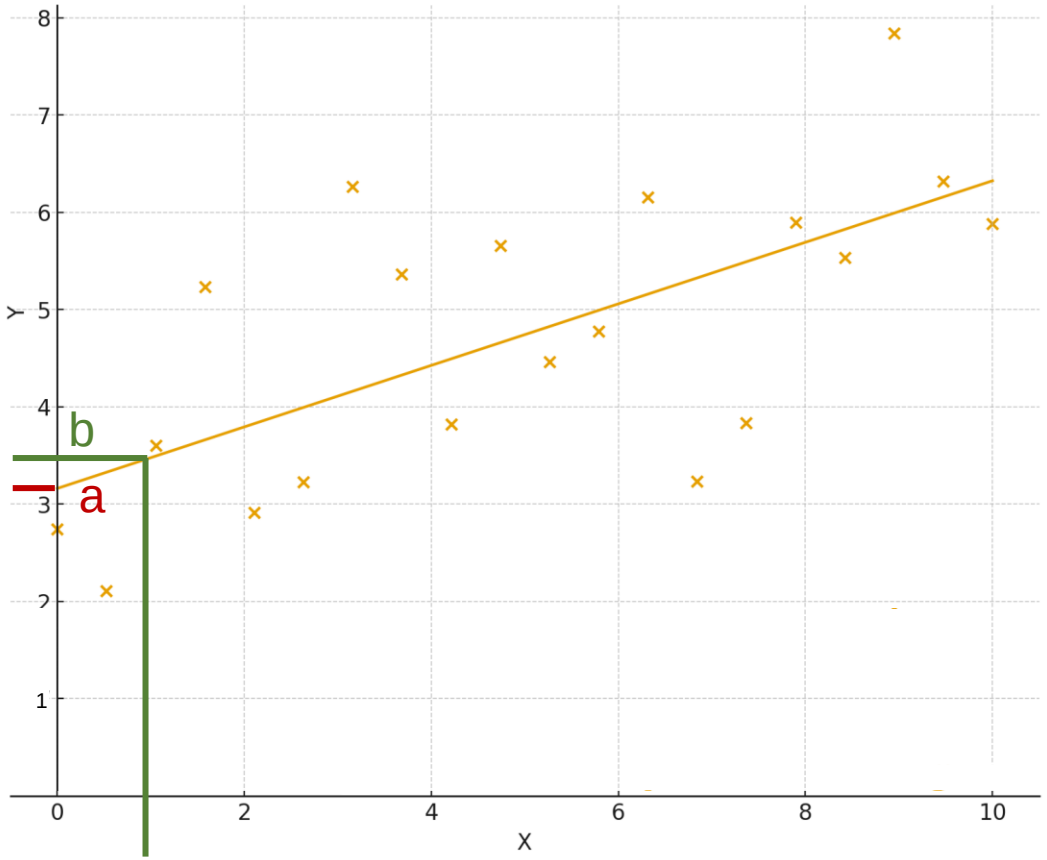
b = Slope (Steigung) = Increase in exam score per hour studied.

For each 1 unit increase in X, Y increases/decreases on average by b units.

- Positive b = increase, positive effect on Y.
- Negative b = decrease, negative effect on Y.

How does a simple linear regression look like?

Example: We model how study time predicts exam performance



X = *Hours of study per week*, Y = *Exam score*

Term	Estimate	Std. Error	Beta	t	p-value
Intercept	3.162	0.503	—	6.280	0.000
h studied	0.316	0.086	0.655	3.674	0.002
R^2	0.429	—	—	—	—
n	20				

(Y = 3.162 + 0.316X).

Without studying, the predicted exam score is 3.16.

For each 1h increase in hours studied, the exam score increases by 0.32.

What do the other outcomes tell me?

Example: We model how study time predicts exam performance

Term	Estimate	Std. Error	Beta	t	p-value
Intercept	3.162	0.503	—	6.280	0.000
h studied	0.316	0.086	0.655	3.674	0.002
R^2	0.429	—	—	—	—
N	20				

Is this effect true or random?

P-value is the probability of getting a result as extreme as (or more extreme than) the observed one, if the null hypothesis were true (e.g. true effect = 0).

→ Small p-value **(< .05)** → reject H_0, significant effect.

- The standard error reflects the uncertainty of b).

  → Smaller SE: more precise estimate.

- Beta is the regression coefficient in standard deviation units.

  → It shows how many SDs Y changes when X increases by one SD.

  → Useful to compare the strength of predictors measured on different scales.

- The t value is the estimate divided by its standard error.

  → Larger t: stronger evidence that true effect is not 0 (H0 is rejected).

What do the other outcomes tell me?

Example: We model how study time predicts exam performance

Term	Estimate	Std. Error	Beta	t	p-value	95% CI
Intercept	3.162	0.503	—	6.280	0.000	[2.10; 4.22]
h studied	0.316	0.086	0.655	3.674	0.002	[0.14; 0.50]
R^2	0.429	—	—	—	—	
N	20					

From the estimate and its SE, we can build a 95% confidence interval.

→ If 0 is not inside the 95% CI, the effect is statistically significant at α = .05.

What do the other outcomes tell me?

Example: We model how study time predicts exam performance

Term	Estimate	Std. Error	Beta	t	p-value
Intercept	3.162	0.503	—	6.280	0.000
h studied	0.316	0.086	0.655	3.674	0.002
R^2	0.429	—	—	—	—
N	20				

Example:

"The model explains 43% of the variance in exam scores."

R^2 shows how much of the variance in Y is explained by the model.

→ It is the proportion of variance in the outcome that can be predicted from the predictor(s).

R^2 ranges from 0 to 1:

→ 0 = the model explains none of the variance.

→ 1 = the model explains all of the variance.

Storks Deliver Babies

(Matthews, 2000)

Country	Area (km^2)	Storks (pairs)	Humans (10^6)	Birth rate (10^3/yr)
Albania	28,750	100	3.2	83
Austria	83,860	300	7.6	87
Belgium	30,520	1	9.9	118
Bulgaria	111,000	5000	9.0	117
Denmark	43,100	9	5.1	59
France	544,000	140	56	774
Germany	357,000	3300	78	901
Greece	132,000	2500	10	106
Holland	41,900	4	15	188
Hungary	93,000	5000	11	124
Italy	301,280	5	57	551
Poland	312,680	30,000	38	610
Portugal	92,390	1500	10	120
Romania	237,500	5000	23	367
Spain	504,750	8000	39	439
Switzerland	41,290	150	6.7	82
Turkey	779,450	25,000	56	1576

Table 1. Geographic, human and stork data for 17 European countries

Surprising correlation:
Regions with more storks also have more newborn babies (r=0.62).

Simple linear regression:

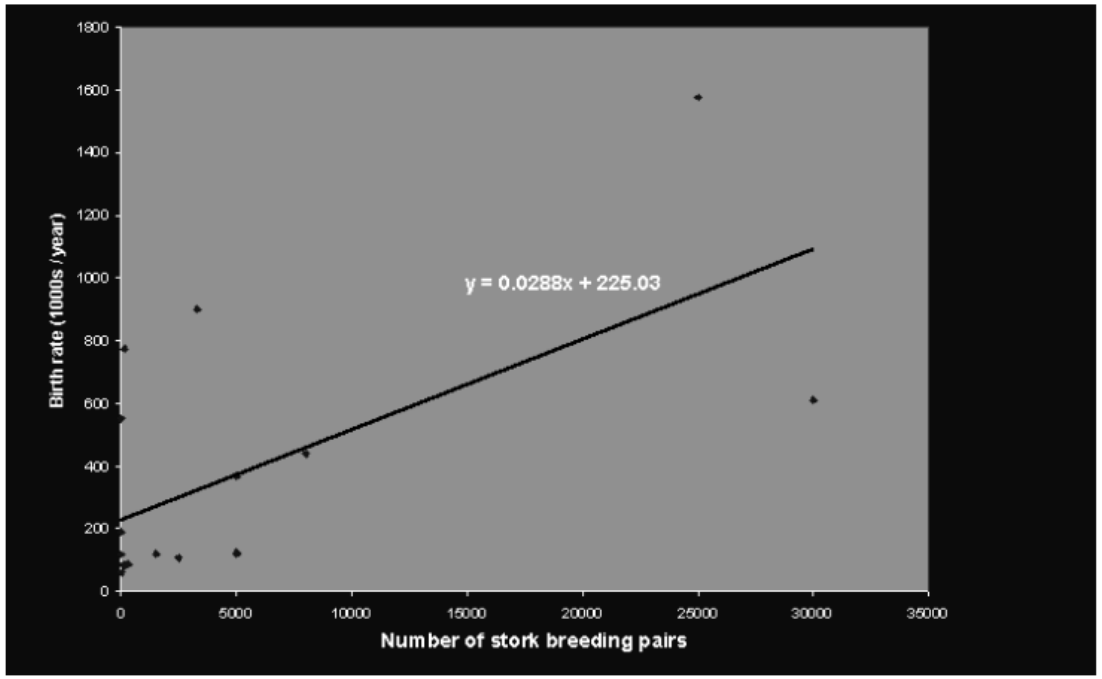


Fig 1. How the number of human births varies with stork populations in 17 European countries.

More storks, more babies.

Storks Deliver Babies

(Matthews, 2000)

Because both stork numbers and birth rates are higher in rural regions than in urban regions.

Once you control for urbanicity, the relationship between storks and babies disappears.

→ It's *not* the storks. It's the type of region.

What is it?

Multivariate statistics deal with the analysis of relationships among three or more variables at the same time.

Why multivariate analyses are important

- **Understand complex relationships**, e.g. how an outcome (income) depends on several predictors at once (education, work experience, gender).
- **Control for confounders** and estimate the *unique* effect of one variable while holding others constant.
- **Improve prediction**, because combining several variables usually predicts outcomes better than a single predictor.

What decisions to make?

1. 🎯 Which variables to include in the model?

Depends on your **research question,** for example:

- What is your **outcome variable**? (e.g., income, satisfaction, voting intention)
- Which variables are your **main predictors**?
- Which variables should you **control for**? (e.g., age, gender, education)
- Are there **potential confounders** that might distort the relationship?
- Do you expect **interaction effects**? (e.g., education × gender)

2. ⚙ Which type of analysis to use?

Depends mainly on the **level of measurement of the outcome variable**

Outcome Variable Y	Suitable analysis
Metric	Multiple linear regression
Categorial binary	Logistic regression

How does a multiple linear regression look like?

Term	Estimate	Std. Error	Beta	t	p-value
Intercept	1512.438	552.317	—	2.738	0.007
training (ref. no)	187.532	228.917	0.058	0.819	0.414
Education: medium (ref. low)	214.759	297.531	0.067	0.722	0.472
Education: high (ref. low)	823.915	321.774	0.243	2.561	0.012
Gender: female (ref. male)	-573.284	219.847	-0.232	-2.608	0.010
Gender: diverse (ref. male)	-917.641	285.392	-0.291	-3.214	0.002
Age in years	41.763	12.311	0.272	3.393	0.001
R^2	0.253	—	—	—	—
Adjusted-R^2	0.223	—	—	—	—
n	150	—	—	—	—

Example: Linear regression on monthly gross income in €

What does the table tell us?

Term	Estimate	Std. Error	Beta	t	p-value
Intercept	1512.438	552.317	—	2.738	0.007

Intercept (1512.44)
When training = 0, age = 0, gender = male and education = low, the expected income is about 1512 €.
(In practice, age = 0 is not meaningful, so the intercept is mostly a technical baseline.)

Gender: female (ref. male)	-573.284	219.847	-0.232	-2.608	0.010
Gender: diverse (ref. male)	-917.641	285.392	-0.291	-3.214	0.002
Age in years	41.763	12.311	0.272	3.393	0.001
R^2	0.253	—	—	—	—
Adjusted-R^2	0.223	—	—	—	—
n	150	—	—	—	—

Example: Linear regression on monthly gross income in €

Multivariate Analyses: Linear Regression

What does the table tell us?

Term	Estimate	Std. Error	Beta	t	p-value
Intercept	1512.438	552.317	—	2.738	0.007
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Age in years	41.763	12.311	0.272	3.393	0.001
R^2	0.253	—	—	—	—
Adjusted-R^2	0.223	—	—	—	—
n	150	—	—	—	—

Training (187.53, n.s.)
Participants who completed the training earn on average about 188 € more than those without training, but this difference is not statistically significant when controlling for age, gender and education.

Example: Linear regression on monthly gross income in €

What does the table tell us?

Term	Estimate	Std. Error	Beta	t	p-value
Intercept	1512.438	552.317	—	2.738	0.007
training (ref. no)	187.532	228.917	0.058	0.819	0.414
Education: medium (ref. low)	214.759	297.531	0.067	0.722	0.472
Education: high (ref. low)	823.915	321.774	0.243	2.561	0.012
n	150	—	—	—	—

Education: medium (214.76, n.s.), high (823.92) vs. low

Persons with medium education earn on average about 215 € more than those with low education, but this difference is not statistically significant when controlling for the other variables.

Persons with high education earn on average about 824 € more than those with low education, controlling for training, age and gender.

Example: Linear regression on monthly gross income in €

Multivariate Analyses: Linear Regression

What does the table tell us?

Term	Estimate	Std. Error	Beta	t	p-value
Intercept	1512.438	552.317	—	2.738	0.007
training (ref. no)	187.532	228.917	0.058	0.819	0.414
Education: medium (ref. low)	214.759	297.531	0.067	0.722	0.472
Education: high (ref. low)	823.915	321.774	0.243	2.561	0.012
Gender: female (ref. male)	-573.284	219.847	-0.232	-2.608	0.010
Gender: diverse (ref. male)	-917.641	285.392	-0.291	-3.214	0.002

Gender: female (–573.28), diverse (–917.64) vs. male

- *Women earn on average about 573 € less than men, controlling for training, age and education.*
- *Persons in the "diverse" category earn on average about 918 € less than men, holding training, age and education constant.*

Example: Linear regression on monthly gross income in €

What does the table tell us?

Term	Estimate	Std. Error	Beta	t	p-value
Intercept	1512.438	552.317	—	2.738	0.007
training (ref. no)	187.532	228.917	0.058	0.819	0.414
Education: medium (ref. low)	214.759	297.531	0.067	0.722	0.472
Education: high (ref. low)	823.915	321.774	0.243	2.561	0.012

Age (41.76)
Holding training, education and gender constant, each additional year of age is associated with about 42 € higher monthly income.

Age in years	41.763	12.311	0.272	3.393	0.001
R^2	0.253	—	—	—	—
Adjusted-R^2	0.223	—	—	—	—
n	150	—	—	—	—

Example: Linear regression on monthly gross income in €

What does the table tell us?

Term	Estimate	Std. Error	Beta	t	p-value
Intercept	1512.438	552.317	—	2.738	0.007
training (ref. no)	187.532	228.917	0.058	0.819	0.414
Education: medium (ref. low)	214.759	297.531	0.067	0.722	0.472
Age in years	41.763	12.311	0.272	3.393	0.001
R^2	0.253	—	—	—	—
Adjusted-R^2	0.223	—	—	—	—
n	150	—	—	—	—

R^2 = 0.2, Adjusted R^2 = 0.225

The model explains about 25% of the variance in income.

The adjusted R^2 corrects R^2 for the number of predictors in the model; here it shows that, after this correction, about 22% of the variance in income is still explained.

Example: Linear regression on monthly gross income in €

Model Comparison: Nested models

	Model 1			Model 2			Model 3		
Term	**Estimate**	**Std. E.**	**p**	**Estimate**	**Std. E.**	**p**	**Estimate**	**Std. E.**	**p**
Intercept	3200.845	450.231	0.000	2850.624	480.512	0.000	1512.438	552.317	0.007
training (ref. no)				311.420	210.531	0.070	187.532	228.917	0.414
edu: med. (ref. low)				260.385	295.784	0.380	214.759	297.531	0.472
edu: high (ref. low)				892.174	320.987	0.004	823.915	321.774	0.012
gender: f (ref. m)							-573.284	219.847	0.010
gender: d (ref. m)							-917.641	285.392	0.002
Age in years							41.763	12.311	0.001
R^2	0.060	—	—	0.170	—	—	0.253	—	—
Adjusted-R^2	0.054	—	—	0.150	—	—	0.223	—	—
n	150	—	—	150	—	—	150	—	—

Example: Linear regression on monthly gross income in €

What does the model comparison tell us?

	Model 1			Model 2			Model 3		
Term	**Estimate**	**Std. E.**	**p**	**Estimate**	**Std. E.**	**p**	**Estimate**	**Std. E.**	**p**
Intercept	3200.845	450.231	0.000	2850.624	480.512	0.000	1512.438	552.317	0.007
training (ref. no)				311.420	210.531	0.070	187.532	228.917	0.414
n	150	—	—	150	—	—	150	—	—

Model 1 (training only):
Training has a clearly positive and significant effect on income

Model 2 (training + education):
When we add education, the training effect becomes smaller and only marginally significant.

Model 3 (training + age + gender + education):
In the full model, the training effect is further reduced and clearly non-significant.

→ *The "training effect" in the simple model was at least partly a confounded effect of education, age and gender.*

Example: Linear regression on monthly gross income in €

What does the model comparison tell us?

Model 1
Training alone explains only about 6% of the variance in income.

Model 2:
Adding education substantially increases explained variance; the model fits the data noticeably better.

Model 3:
Including age and gender further improves model fit; together the predictors explain about a quarter of the variance in income.

→ *Adding theoretically relevant control variables makes the model more realistic and clearly increases its explanatory power, even though the original training effect becomes non-significant.*

	Model 1			Model 2			Model 3		
Age in years									
R^2	0.060	—	—	0.170	—	—	0.253	—	—
Adjusted-R^2	0.054	—	—	0.150	—	—	0.223	—	—
n	150	—	—	150	—	—	150	—	—

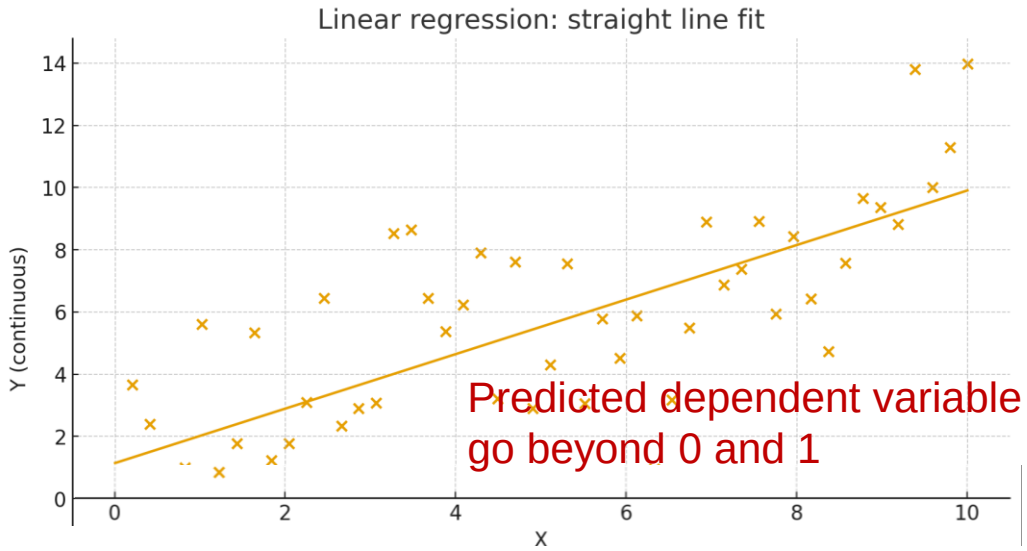
Example: Linear regression on monthly gross income in €

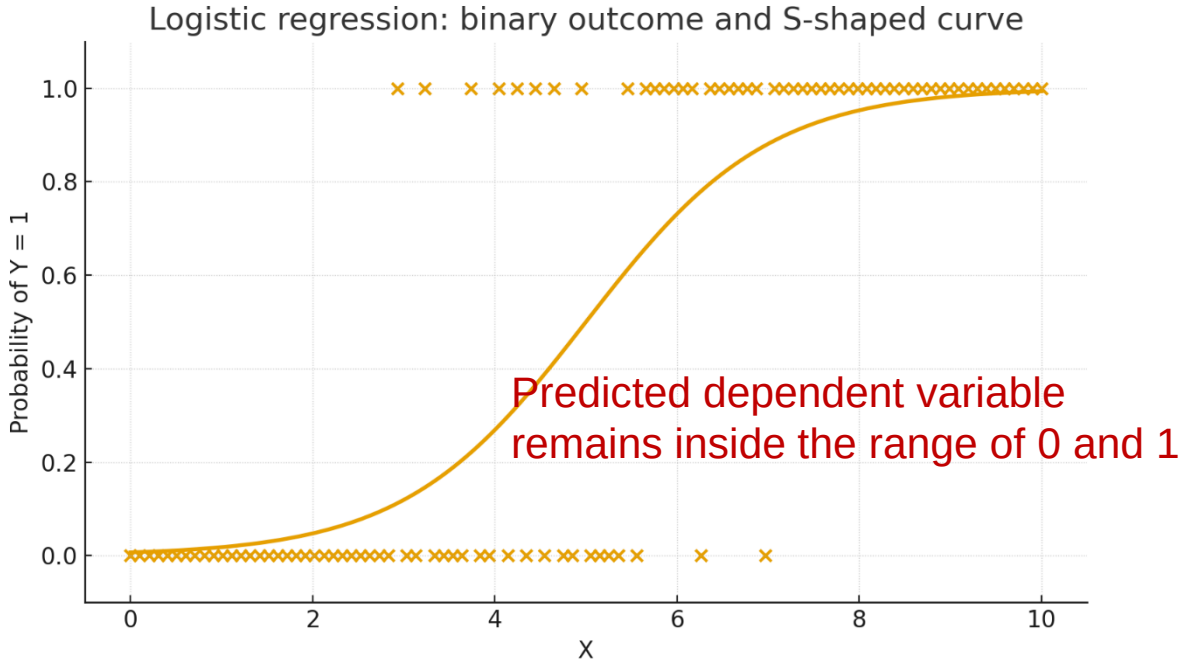
Linear regression: Assumptions

Linear regressions require:

- Dependent variable is metric.
  → Use logistic regression for categorial binary variables.
- Relationship between predictors and outcome is (approximately) linear.
- Residuals have constant variance (homoscedasticity).
- Residuals are approximately normally distributed.
- No strong multicollinearity, that means predictors are not (highly) redundant (e.g. age and years of education).

Linear vs logistic regression





Linear regression

Outcome **Y is metric/continuous** (e.g. income, test score).

Models a **straight-line relationship** between X and Y.

Logistic regression

Outcome **Y is categorical binary** (0/1, e.g. PhD started: yes/no).

Models a **curved, S-shaped relationship** between X and the **probability** of Y = 1.

How does a logistic regression look like?

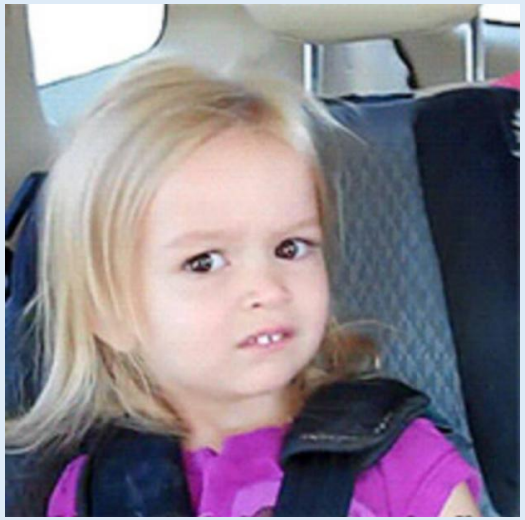
Term	Estimate	Std. Error	z	p-value
Intercept	-2.90	0.80	-3.63	0.000

Estimate for a predictor

How much the log-odds of Y = 1 change, if X_j increases by 1 unit, holding other variables constant.

Odds of an event are $odds = \frac{p}{1-p}$,
where p is the probability that the event happens.

Log-odds are the natural logarithm of the odds
log-odds= $\log(\frac{p}{1-p})$.



Age at graduation in years	-0.047	0.021	-2.26	0.024
Pseudo-R^2	0.18	—	—	—
n	450	—	—	—

Example: Logistic regression on PhD started (0 = no, 1 = yes)

Linear regression: Odds Ratios

Odds ratio (OR) compares how likely an event is in one group (or at one value of a predictor) to how likely it is in another.

$$OR = \frac{Odds\ in\ group\ 1}{Odds\ in\ group\ 2}$$

For categorical predictors, group 1 is the category you are estimating the effect for (e.g. “yes”, “female”), and group 2 is the reference category. The odds ratio compares the odds in group 1 to the odds in group 2.

For continuous predictors, the odds ratio compares the odds at X + 1 unit (group 1) to the odds at X (group 2), e.g. With each additional year of age, the odds of starting a PhD are multiplied by 0.95 (i.e. they decrease by about 5%).

OR = 1 → no difference in odds between the groups.

OR > 1 → higher odds in the first group (event is more likely).

OR < 1 → lower odds in the first group (event is less likely).

Multivariate Analyses: Logistic Regression

What does the table tell us?

Term	OR	Std. Error	z	p-value
Intercept	0.06	0.80	-3.63	0.000
Worked as RA (ref. no)	2.51	0.27	3.41	0.001

Worked as RA (OR = 2.51)
*Graduates who worked as a research assistant (RA) have about **2.5 times higher odds** of starting a PhD than graduates who did not work as an RA, **controlling for discipline, final grade, gender and age**.*
*→ RA experience is associated with a **significant higher chance** of starting a PhD.*

Gender: female (ref. male)	0.71	0.24	-1.46	0.144
Gender: diverse (ref. male)	0.33	0.40	-2.75	0.006
Age at graduation in years	0.95	0.021	-2.26	0.024
Pseudo-R^2	0.18	—	—	—
n	450	—	—	—

Example: Logistic regression on PhD started (0 = no, 1 = yes)

Multivariate Analyses: Logistic Regression

What does the table tell us?

Term	OR	Std. Error	z	p-value
Intercept	0.06	0.80	-3.63	0.000
Worked as RA (ref. no)	2.51	0.27	3.41	0.001
Final grade (“very good” vs “worse”)	2.34	0.25	3.40	0.001
Discipline: social sciences (ref. nat.)	0.74	0.29	-1.03	0.302
Discipline: humanities (ref. nat.)	0.43	0.33	-2.58	0.000
Discipline: health sciences (ref. nat)	1.16	0.34	0.44	0.662

Social sciences (OR = 0.74), Humanities (OR = 0.43)

*Graduates from the **social sciences** have about **0.74 times the odds** of starting a PhD compared to graduates from the **natural sciences**, controlling for RA experience, grade, gender and age (this difference is not statistically significant).*

*Graduates from the **humanities** have only about **0.43 times the odds** of starting a PhD compared to **natural sciences** graduates – that is, their odds are clearly lower, even after controlling for RA experience, grade, gender and age….*

Example: Logistic regression on PhD started (0 = no, 1 = yes)

Multivariate Analyses: Logistic Regression

What does the table tell us?

Term	OR	Std. Error	z	p-value
Intercept	0.06	0.80	-3.63	0.000
Worked as RA (ref. no)	2.51	0.27	3.41	0.001
Final grade (“very good” vs “worse”)	2.34	0.25	3.40	0.001
Discipline: social sciences (ref. nat.)	0.74	0.29	-1.03	0.302
Discipline: humanities (ref. nat.)	0.43	0.33	-2.58	0.000

Age at graduation (OR = 0.95)

*For each additional year of age at graduation, the odds of starting a PhD are multiplied by about **0.95**, that is, they **decrease by roughly 5% per year**, controlling for discipline, RA experience, grade and gender.*

Age at graduation in years	0.95	0.021	-2.26	0.024
Pseudo-R^2	0.18	—	—	—
n	450	—	—	—

Example: Logistic regression on PhD started (0 = no, 1 = yes)

Pseudo-R^2

In linear regression, R^2 is based on explained variance in a continuous outcome and a clean decomposition of total variance (SS total = SS explained + SS residual).

In logistic regression, the outcome is binary, the model works and we do not have the same variance decomposition.

→ Instead, we use pseudo R^2 measures (e.g. McFadden, Cox–Snell, Nagelkerke) that compare the fitted model to a null model (with no predictors) based on likelihoods.

→ They show **how much better** the model fits compared to a model without predictors, **not** the exact "percentage of variance explained".

→ Pseudo R^2 values are usually **much smaller** than R^2 in linear regression (e.g. 0.10–0.30 can already indicate a useful model).

Multivariate Analyses: Logistic Regression

What does the table tell us?

Term	OR	Std. Error	z	p-value
Intercept	0.06	0.80	-3.63	0.000
Worked as RA (ref. no)	2.51	0.27	3.41	0.001
Final grade (“very good” vs “worse”)	2.34	0.25	3.40	0.001
Discipline: social sciences (ref. nat.)	0.74	0.29	-1.03	0.302
Discipline: humanities (ref. nat.)	0.43	0.33	-2.58	0.000

Pseudo-R^2

The pseudo-R^2 of 0.18 suggests that the logistic regression model provides a modest improvement in explaining who starts a PhD compared to a model without predictors.

Age at graduation in years	0.95	0.021	-2.26	0.024
Pseudo-R^2	0.18	—	—	—
n	450	—	—	—

Example: Logistic regression on PhD started (0 = no, 1 = yes)

Your turn!

1. Copy folder `Materials` from to your local machine

   → https://github.com/Data-Science-Center-UB/Intro-Quantitative-Analysis-R

   → Path do subfolder `Exercises` will be your **working directory**

   → Folder content: data sets, exercises without & with solution

2. Do exercise **“04_qa_multi_ex”**

   Version with solution: **04_qa_multi_ex_solution**

Wrap-up

What we did not cover today….

- Variable transformation
- Factor Analysis
- Missing values: Imputation
- Interaction effects
- Multinomial logistic regression
- Model comparison in logistic regression, Average Marginal Effects
- Event-History-/ Survival-Analysis: censored data, time-varying covariates
- Visualization

….

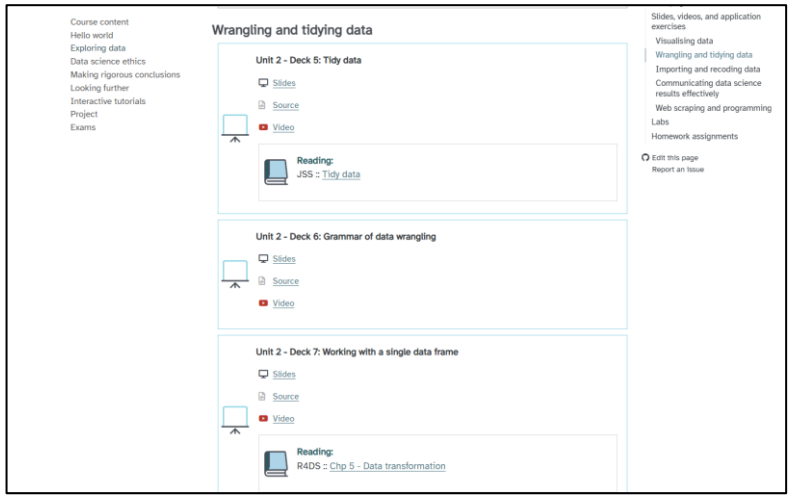
Resources

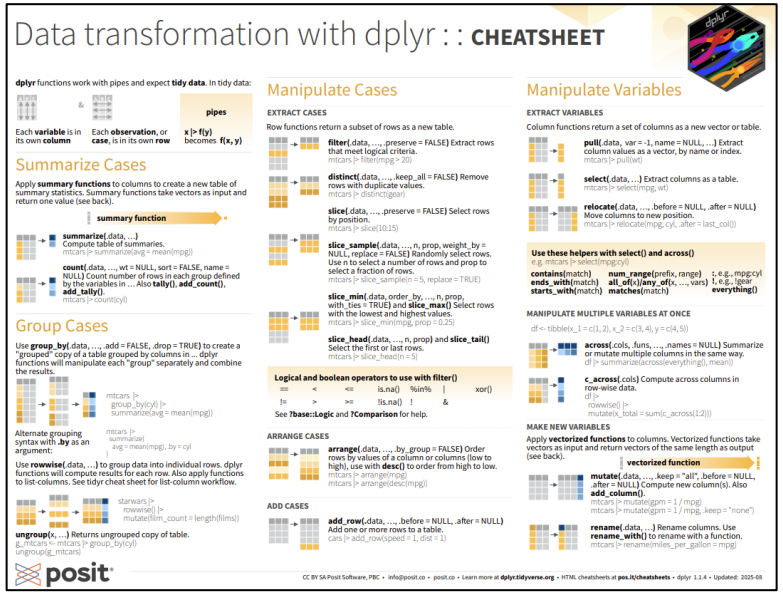
Self-Learning Tool

https://datasciencebox.org/

Cheat Sheets

https://posit.co/resources/cheatsheets/





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10/11.12 **Applied Statistical Learning using R**

1112. **Introduction to Python for Qualitative Research**

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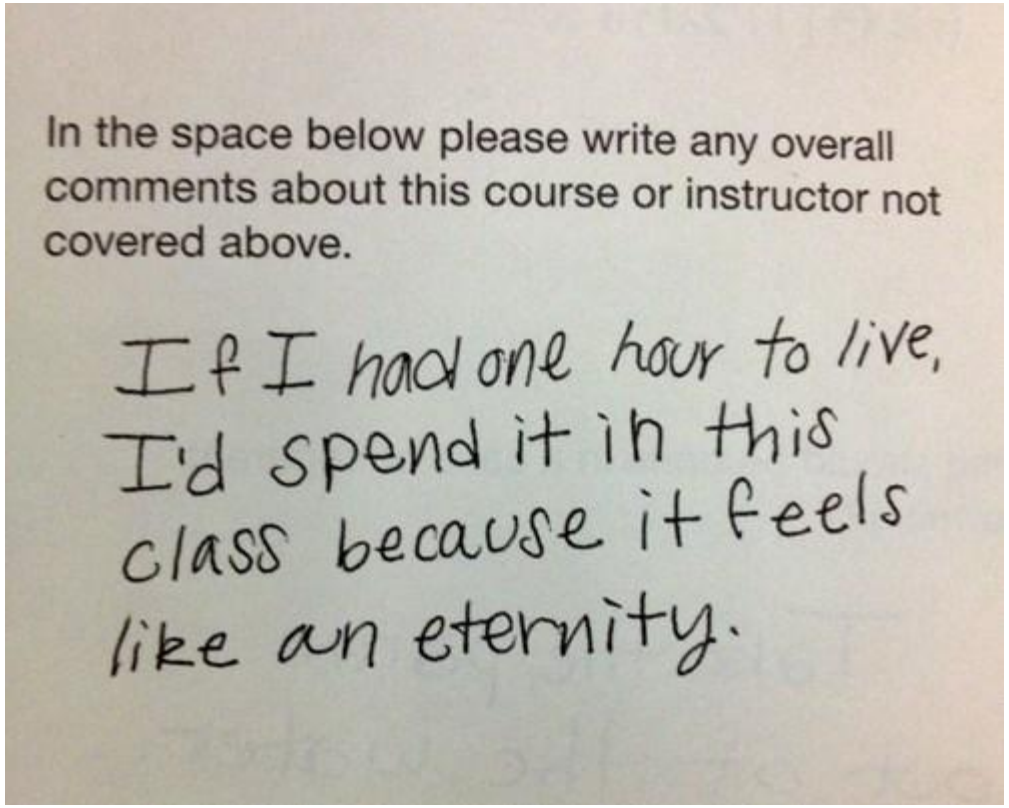
- Overview of DataNord **trainings**, **networking opportunities and other events** in the next month
- Additional announcements

Evaluation



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Thank You for Your Participation!

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