Data preparation

Theoretical and Empirical Research Methodology,
Implementation Lab 6

Prof. Dr. Claudius Gräbner-Radkowitsch
Europa-University Flensburg, Department of Pluralist Economics
www.claudius-graebner.com | @ClaudiusGraebner | claudius@claudius-graebner.com

Europa-Universität Flensburg

Europa-Universität Flensburg
International Institute of Management and Economic Education
Department of Pluralist Economics

Goals for today

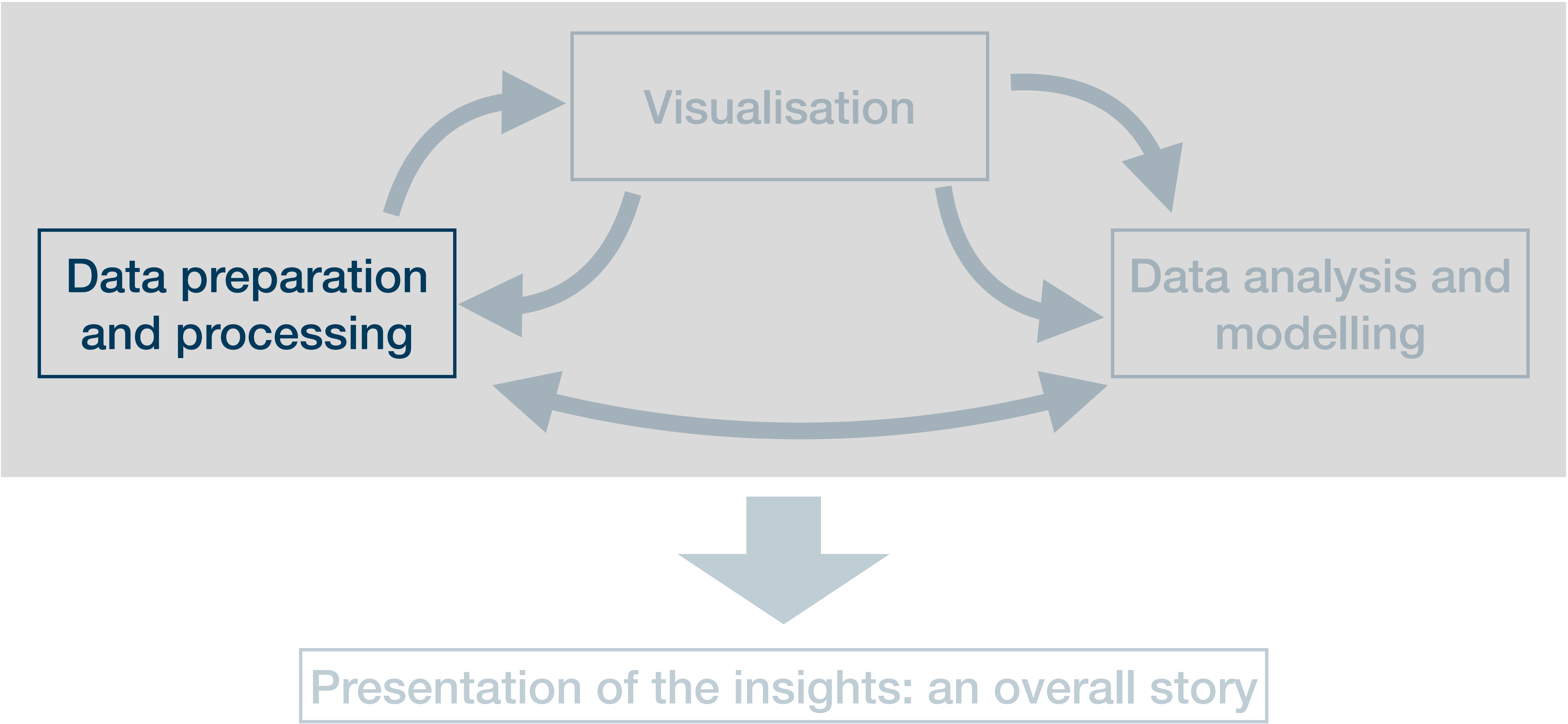
I. Understand the concept of tidy data

II. Get an overview over the most common transformation routines

III. Master a number of functions from the `tidyr` and `dplyr` packages to address some of these challenges

The role of data preparation

- Importing and preparing is the most fundamental task in data science
  - It is also largely under-appreciated 🙄



What is tidy data?

The goal: tidy data

> Tidy datasets are all alike, but every messy dataset is messy in its own way.
>
> Hadley Wickham

- Translation into plain English:
  - We find data sets in all kind of ***-up forms in the world
  - We must turn them into a form that's a good starting point for any further tasks
- Good thing: this form is unique – and its called **tidy**

The goal: tidy data

Every **column** corresponds to one and only one **variable**

```
# A tibble: 4 × 4
  c_code  year exports unemployment
  <chr>  <int>   <dbl>        <dbl>
1 AT      2013    53.4         5.34
2 AT      2014    53.4         5.62
3 DE      2013    45.4         5.23
4 DE      2014    45.6         4.98
```

Every **row** corresponds to one and only one **observation**

Every **cell** corresponds to one and only one **value**

- Every data set that satisfies these three demands is called tidy
- Excellent start for basically every further task – but maybe not the best way to represent data to humans

The goal: tidy data

Every **row** corresponds to one and only one **observation**

Every **column** corresponds to one and only one **variable**

Every **cell** corresponds to one and only one **value**

```
# A tibble: 2 × 4
  c_code variable     `2013` `2014`
  <chr>  <chr>         <dbl>  <dbl>
1 AT     unemployment   5.34   5.62
2 DE     unemployment   5.23   4.98
```

```
# A tibble: 4 × 4
  c_code  year exports variable
  <chr>  <int>   <dbl> <chr>
1 AT      2013    53.4 exports
2 AT      2014    53.4 exports
3 DE      2013    45.4 exports
4 DE      2014    45.6 exports
```

```
# A tibble: 2 × 2
  country important_industries
  <chr>   <chr>
1 DE      Cars (25%) and meat (10%)
2 AT      Wine (5%) and milk (2%)
```

- The goal of data wrangling is to turn such untidy data into tidy data

Recap questions

- What are the three demands a data set needs to fulfil to count as ‘tidy’?
- Why do we care about tidy data at all?
- Are there plausible reasons for transforming a tidy data set into a non-tidy data set?
- Consider the following data sets. Are they tidy? If not, what would you need to change to make them tidy?

A tibble: 1 × 4

	country	growth_2018	growth_2019	growth_2020
	<chr>	<dbl>	<dbl>	<dbl>
1	Germany	1.09	1.06	-4.57

A tibble: 6 × 2

	VarName	Value
	<chr>	<dbl>
1	beer_consumption	81.7
2	beer_price	1.78
3	personal_income	25088
4	beer_consumption	56.9
5	beer_price	2.27
6	personal_income	26561

A tibble: 6 × 3

	beer_consumption	liquor_price	water_price
	<dbl>	<dbl>	<dbl>
1	81.7	6.95	1.11
2	56.9	7.32	0.67
3	64.1	6.96	0.83
4	65.4	7.18	0.75
5	64.1	7.46	1.06
6	58.1	7.47	1.1

The way to tidy data

> “Tidy datasets are all alike, but every messy dataset is messy in its own way.”
>
> Hadley Wickham

- The starting point to tidy data is always different
- The goal is always the same → so are the steps: **six main routines**
- Two main packages are relevant:
  - `tidyr` provides functions for **reshaping data** into tidy format (‘wrangling’)
  - `dplyr` provides functions for **manipulating data** to extract desired information

The six routines of data preparation

Reshaping data from long to wide format (and vice versa)

```
# A tibble: 4 × 4
  c_code  year exports unemployment
  <chr>  <int>   <dbl>        <dbl>
1 AT      2013    53.4         5.34
2 AT      2014    53.4         5.62
3 DE      2013    45.4         5.23
4 DE      2014    45.6         4.98
```

↔

```
# A tibble: 8 × 4
  c_code  year variable     value
  <chr>  <int> <chr>        <dbl>
1 AT      2013 exports      53.4 
2 AT      2013 unemployment  5.34
3 AT      2014 exports      53.4 
4 AT      2014 unemployment  5.62
5 DE      2013 exports      45.4 
6 DE      2013 unemployment  5.23
7 DE      2014 exports      45.6 
8 DE      2014 unemployment  4.98
```

The six routines of data preparation

Filter rows according to conditions

```
# A tibble: 4 × 4
  c_code  year exports unemployment
  <chr>  <int>   <dbl>        <dbl>
1 AT      2013    53.4         5.34
2 AT      2014    53.4         5.62
3 DE      2013    45.4         5.23
4 DE      2014    45.6         4.98
```

```
# A tibble: 2 × 4
  c_code  year exports unemployment
  <chr>  <int>   <dbl>        <dbl>
1 DE      2013    45.4         5.23
2 DE      2014    45.6         4.98
```

The six routines of data preparation

Select columns/variables

```
# A tibble: 4 × 4
  c_code  year exports unemployment
  <chr>  <int>   <dbl>        <dbl>
1 AT      2013    53.4         5.34
2 AT      2014    53.4         5.62
3 DE      2013    45.4         5.23
4 DE      2014    45.6         4.98
```

```
# A tibble: 4 × 3
  c_code  year exports
  <chr>  <int>   <dbl>
1 AT      2013    53.4
2 AT      2014    53.4
3 DE      2013    45.4
4 DE      2014    45.6
```

The six routines of data preparation

Mutate or create variables

```
# A tibble: 2 × 4
  c_code variable     `2013` `2014`
  <chr>  <chr>         <dbl>  <dbl>
1 AT     unemployment   5.34   5.62
2 DE     unemployment   5.23   4.98
```

```
# A tibble: 2 × 5
  c_code variable     `2013` `2014` change
  <chr>  <chr>         <dbl>  <dbl>  <dbl>
1 AT     unemployment   5.34   5.62  0.285
2 DE     unemployment   5.23   4.98 -0.25
```

The six routines of data preparation

```
# A tibble: 4 × 4
  c_code  year exports unemployment
  <chr>  <int>   <dbl>        <dbl>
1 AT      2013    53.4         5.34
2 AT      2014    53.4         5.62
3 DE      2013    45.4         5.23
4 DE      2014    45.6         4.98
```

↓

```
# A tibble: 2 × 3
  c_code exports_avg unemployment_avg
  <chr>        <dbl>            <dbl>
1 AT            53.4             5.48
2 DE            45.5             5.11
```

Group and **summarise** data

The six routines of data preparation

```
# A tibble: 4 × 3
  c_code  year exports
  <chr>  <int>   <dbl>
1 AT      2013    53.4
2 AT      2014    53.4
3 DE      2013    45.4
4 DE      2014    45.6
```

```
# A tibble: 4 × 3
  c_code  year unemployment
  <chr>  <int>        <dbl>
1 AT      2013         5.34
2 AT      2014         5.62
3 DE      2013         5.23
4 DE      2014         4.98
```

```
# A tibble: 4 × 4
  c_code  year exports unemployment
  <chr>  <int>   <dbl>        <dbl>
1 AT      2013    53.4         5.34
2 AT      2014    53.4         5.62
3 DE      2013    45.4         5.23
4 DE      2014    45.6         4.98
```

Merge several data sets

The six routines of data preparation

- After having imported your data into R, you can usually make it tidy using a sequential combination of the following routines:

Reshaping data from long to wide format (and vice versa)	**Mutate** or create variables
Filter rows according to conditions	**Group** and **summarise** data
Select columns/variables	**Merge** several data sets

- With these six routines, you can prepare almost any messy data set
- This way you produce the inputs we used for visualisation…
  - …and the inputs we will use for modelling

Recap questions

- What is the relation between long and wide data sets?
- Name the six main routines of data preparation and explain what they are used for.
- What does ‘data wrangling’ mean?
- Which two packages are used most frequently in the context of data preparation? What are their respective areas of application?

Six main routines for data preparation

Session content

- We will go through the following challenges via direct demonstration:

Filter rows according to conditions	**Mutate** or create variables
Reshaping data from long to wide format (and vice versa)	**Group** and **summarise** data
Select columns/variables	**Merge** several data sets

- For documentation purposes check out the lecture notes and the readings
  - The data sets used for the following exercises are all contained in `wrangling_exercises_data.zip`, which is available on the course homepage

Short recap on reshaping

- Take the data set `data_raw_long.csv` and transform it as follows:

```
> data_raw_long
   country year variable    value
1: Germany 2017    unemp     3.75
2: Germany 2017      gdp 53071.46
3: Germany 2018    unemp     3.38
4: Germany 2018      gdp 53431.39
5:  Greece 2017    unemp    21.49
6:  Greece 2017      gdp 28604.86
7:  Greece 2018    unemp    19.29
8:  Greece 2018      gdp 29141.17
```

```
# A tibble: 4 × 4
   year variable  Germany  Greece
  <int> <chr>       <dbl>   <dbl>
1  2017 unemp        3.75    21.5
2  2017 gdp      53071.   28605.
3  2018 unemp        3.38    19.3
4  2018 gdp      53431.   29141.
```

- Take the data set `data_raw_wide.csv` and transform it as follows:

```
> data_raw_wide
# A tibble: 2 × 3
  country `2017` `2018`
  <chr>    <dbl>  <dbl>
1 Germany   29.4   29.6
2 Greece    32.2   31.7
```

```
# A tibble: 4 × 3
  country year   gini
  <chr>   <chr> <dbl>
1 Germany 2017   29.4
2 Germany 2018   29.6
3 Greece  2017   32.2
4 Greece  2018   31.7
```

Short recap on manipulation basics

- Consider the data set `wine2dine` from the package `DataScienceExercises`

1. Filter the data set such that it only contains white wines
2. Then remove the column '`kind`'
3. Change the type of the column '`quality`' into `double`
4. Divide the values in the columns '`alcohol`' and '`residual sugar`' by 100
5. Filter the data such that you only keep the wines with the highest quality score

Short recap on summarising and grouping

- What is the difference between `dplyr::mutate()` and `dplyr::summarize()`?

- Consider again the data set `wine2dine` from the package `DataScienceExercises`

1. Summarise the data by computing the mean alcohol, mean sugar, and mean quality of white and red wines

2. Compute a variable indicating how the quality of each wine deviates from the average quality of all wines.

Short recap on joining data sets

- Consider the data sets `join_x.csv` and `join_y.csv` and join them on the columns `time` and `id` using the functions `left_join()`, `right_join()`, and `full_join()`!

- Try for yourself what the function `inner_join()` does. How does it differ from `left_join()`, `right_join()`, and `full_join()`?

- Consider the data sets `join_x.csv` and `join_y.csv` and the function `dplyr::full_join()`. What is the difference of joining on columns `time` and `id` vs joining only on column `id`?

Helpful tools I: Pipes

Using pipes

- While not strictly necessary, you can improve the usability and readability of your code using so called pipes: `%>%`
- Pipes take the result from their left and 'throw' them on the right
  - The thrown result can be referred to via `.`
  - Usually they are used at the end of a line and 'throw' the result of one line into the next one

```r
data_sub <- dplyr::select(
  .data = data_raw,
  country, year, unemp, gdp)
```

↔

```r
data_sub <- data_raw %>%
  dplyr::select(
    .data = .,
    country, year, unemp, gdp)
```

Using pipes

- While not strictly necessary, you can improve the usability and readability of your code using so called pipes: `%>%`
- Pipes take the result of one line and 'throw' them into the next line
  - The thrown result can be referred to via `.`
  - By default, the thrown result is used as the first argument of the function in the next line

```
data_sub <- dplyr::select(
  .data = data_raw,
  country, year, unemp, gdp)
```

```
data_sub <- data_raw %>%
  dplyr::select(
    .data = .,
    country, year, unemp, gdp)
```

```
data_sub <- data_raw %>%
  dplyr::select(
    country, year, unemp, gdp)
```

Using pipes

- A more practical example:

```
chain_1 <- tidyr::pivot_longer(
  data = data_raw_wide,
  cols = c("gdp", "gini","unemp"),
  names_to = "indicator",
  values_to = "val")
```

```
chain_2 <- tidyr::pivot_wider(
  data = chain_1,
  names_from = "year",
  values_from = "val")
```

```
chain_complete <- pipe_data_raw %>%
  tidyr::pivot_longer(
    data = .,
    cols = c("gdp", "gini", "unemp"),
    names_to = "indicator",
    values_to = "val") %>%
  tidyr::pivot_wider(
    data = .,
    names_from = "year",
    values_from = "val")
```

- Pipes make code almost always easier to read → desired stage at the end
- But is is usually easier make intermediate steps explicit during code development

Short recap on piping

- Explain what the pipe `%>%` does.
- When can the pipe be useful?
- Should you develop code with pipes right from the start? Why? Why not?
- Rewrite the following code 👉 using pipes (data available via course page)

```
pipedata_v1 <- data.table::fread(here("data/recap2.csv"))

pipedata_v2 <- tidyr::pivot_longer(
  data = pipedata_v1,
  cols = c("lifeExp", "gdpPercap"),
  names_to = "Indicator",
  values_to = "Value")

pipedata_v3 <- tidyr::pivot_wider(
  data = pipedata_v2,
  names_from = "year",
  values_from = "Value")
```

- Look at the introduction to the R package **`magrittr`**, which defines even more pipes: https://magrittr.tidyverse.org/articles/magrittr.html

Helpful tools II: Selection helpers

Digression: tidy selection helpers

- It can become tedious to select many columns using explicit reference to their names

- The tidy selection helpers are a useful tool to select columns based on common criteria:

```
data_raw_wide %>%
  dplyr::select(gdp, gini)
```

```
data_raw_wide %>%
  dplyr::select(
    tidyr::starts_with("g"))
```

Combine multiple selectors

```
data_raw_wide %>%
  dplyr::select(c(
    tidyr::all_of(c("country", "year")),
    tidyr::starts_with("g")))
```

- For a complete list of helpers see, e.g., the official reference

Exercise 1: filtering and reshaping

- Use the data set `exercise_1.csv` contained in `wrangling_exercises_data.zip`

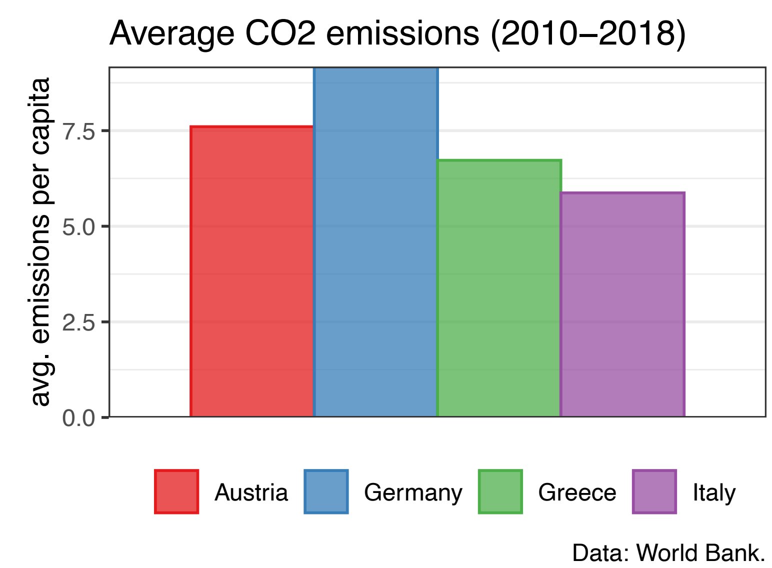
- Import the data and …
  - …only consider data on Greece and Germany between 1995 and 2015
  - …make it wider (and tidy) 👉
  - …save it in the subfolder `data/tidy/`

```
# A tibble: 42 × 4
   country  year    gdp   co2
   <chr>   <int>  <dbl> <dbl>
 1 Germany  1995 39366. 10.7
 2 Germany  1996 39569. 11.0
 3 Germany  1997 40219. 10.6
 4 Germany  1998 41023. 10.5
 5 Germany  1999 41770. 10.2
 6 Germany  2000 42928. 10.1
 7 Germany  2001 43577. 10.3
 8 Germany  2002 43417. 10.1
 9 Germany  2003 43089. 10.1
10 Germany  2004 43605.  9.95
# … with 32 more rows
```

Exercise 2: mutating, selecting & summarising

- Use the data set `exercise_2.csv` contained in `wrangling_exercises_data.zip`
- Import the data
  - Only keep the variables `gdp`, `share_indus`, and `co2`
  - Divide the industry share in GDP with 100
  - Only keep data between 2010 and 2018
  - Compute the averages over time for all countries
- Bonus:
  - Visualise the resulting CO2 average via a bar plot

```
# A tibble: 12 × 3
   country indicator   time_avg
   <chr>   <chr>          <dbl>
 1 Austria co2             7.60
 2 Austria gdp         53322.
 3 Austria share_indus     0.254
 4 Germany co2             9.17
 5 Germany gdp         50781.
 6 Germany share_indus     0.272
 7 Greece  co2             6.72
 8 Greece  gdp         29169.
 9 Greece  share_indus     0.144
10 Italy   co2             5.87
11 Italy   gdp         41326.
12 Italy   share_indus     0.213
```



Summary & outlook

Summary

- After importing raw data you usually must prepare them → make **tidy**
- Tidy data is the input to any visualisation/modelling task and defined as data where:
  - Every **column** corresponds to one and only one **variable**
  - Every **row** corresponds to one and only one **observation**
  - Every **cell** corresponds to one and only one **value**
- It is usually a good idea to write a script that imports raw, and saves tidy data
- Such script usually makes use of functions from the following packages:
  - `data.table`, `dplyr`, `tidyr`, and `here`

Summary

- These packages provide functions that help you to address some wrangling challenges that regularly await you:
  - Reshaping data: `tidyr::pivot_longer()` and `tidyr::pivot_wider()`
  - Filtering rows: `dplyr::filter()`
  - Selecting columns: `dplyr::select()` and the select helpers
  - Mutating or creating variables: `dplyr::mutate()`
  - Grouping and summarising: `dplyr::group_by()` and `dplyr::summarise()`
  - Merging data sets: `dplyr::*_join()`
- In later sessions we will learn also about some convenience shortcuts

General recap questions

- What are the three demands a data set needs to fulfil to count as ‘tidy’?
- Why do we care about tidy data at all?
- What is the relation between long and wide data sets?
- What are the six main routines of data preparation? What are they used for?
- What does ‘data wrangling’ mean?
- Which two packages are used most frequently in the context of data preparation? What are their respective areas of application?
- Explain what the pipe `%>%` does. When can the pipe be useful?

Data preparation is mainly about practice, so the practical exercises are particularly recommended 👩🏼‍💻👨🏾‍💻