Data preparation

Applied Data Science using R

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Goals for today

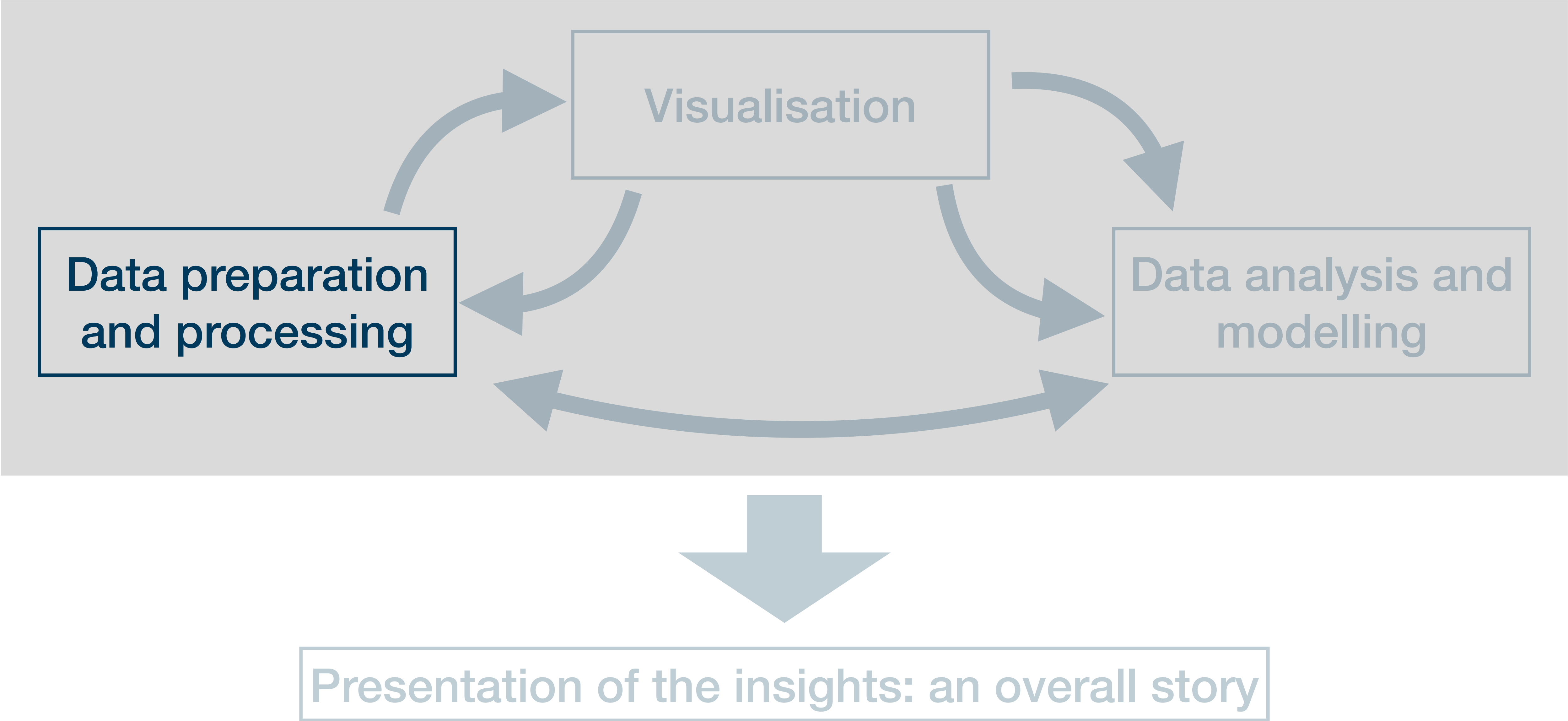
I. Understand the concept of tidy data

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 x 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` 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 `gini_join` and transform it as follows:

```
> gini_join
# A tibble: 2 × 3
  country  year  gini
  <chr>   <int> <dbl>
1 Greece   2015  33.1
2 Greece   2017  32.2
```

```
# A tibble: 2 × 4
  country  year Indicator Observation
  <chr>   <int> <chr>           <dbl>
1 Greece   2015 gini             33.1
2 Greece   2017 gini             32.2
```

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`

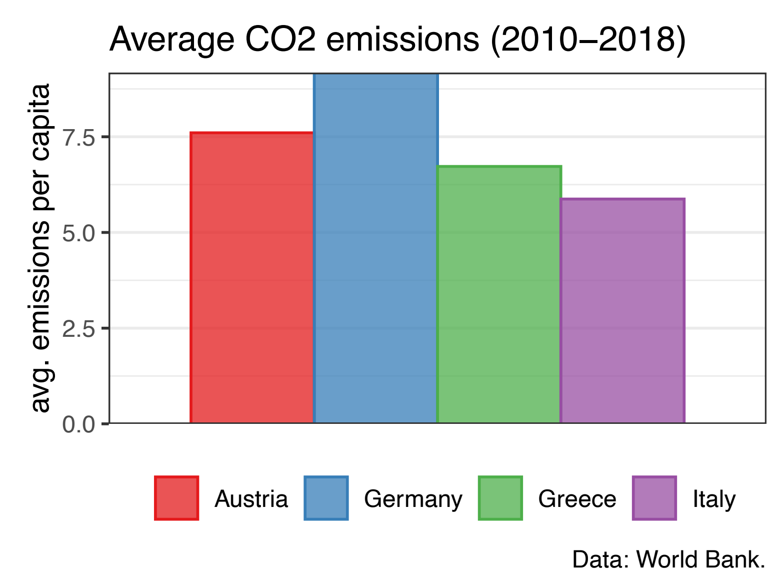
- Import the data and …
  - …only consider data on Greece and Germany between 1995 and 2015
  - …make it wider (and tidy) 👉
  - …save it in the subfolder `data/tidy/`

```
# 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 👩🏼‍💻👨🏾‍💻