Data preparation

An introduction to R, day 2

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Learning goals

I. Clarify questions on day 1

II. Learn how to import csv files using the function `data.table::fread()`

III. Clarify the process of data preparation and the concept of tidy data

IV. Get an overview over the most common transformation routines and the corresponding functions from the **`tidyr`** and **`dplyr`** packages

Recap day 1

- R is a **high-level programming language** with dialects, R Studio an IDE
- R **packages** as a way to expand the capabilities of base R
- For your projects use R **projects**, a clear **folder structure** and the **here package**
- “Everything that exists is an object, everything that happens is a function call.”
- **Four basic object types**, advanced ones as modifications of the basic types

Questions?

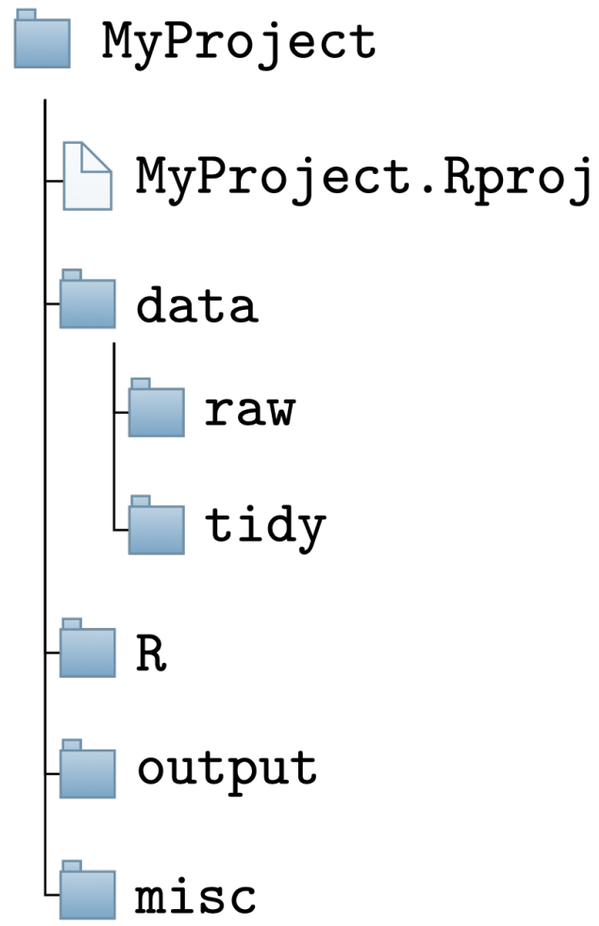
Import data

Preparation: set up your working environment

See separate session on project management

- Raw data should be saved in `data/raw`
- Tidied up data should be saved in `data/tidy`
  → keep it separate

See upcoming topic on data preparation!



Your turn:

Set up a working environment, download the data sets `fread_expls.zip` from the homepage and save them in the right folder.

Import functions

- Once set up the project environment you can import data
  - Assume that your raw data is stored in the folder **`data/raw`**
- The right function to import a data set depends on the file type:

csv/tsv files	.Rds/RData files	Specific formats

`data.table::fread()`	`readRDS()`
	`load()`
		`haven::read_dta()`
		`haven::read_sas()`
		`haven::read_spss()`

- Basic procedure the same in all cases → focus on reading **`csv`** files here

How to import data

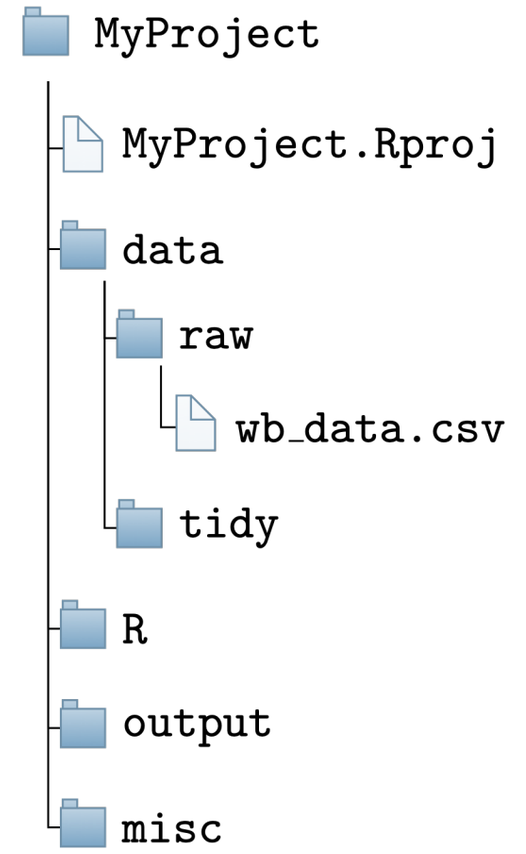
- Good practice: save path to file in a vector:

```
data_path <- here::here("data/raw/wb_data.csv")
```

- csv file → `data.table::fread()`:

```
data.table::fread(file = data_path)
data.table::fread(
   file = here::here("data/raw/wb_data.csv"))
```

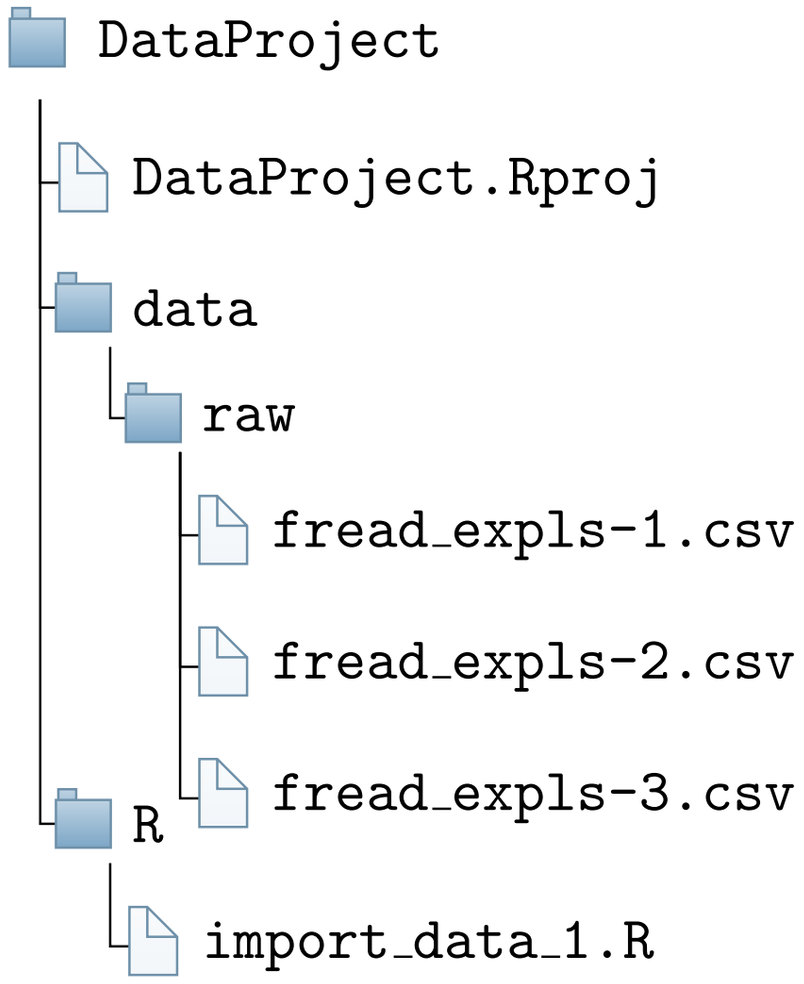
- This uses default options to import the file
  - Works often for clean data files
  - For not so clean data files we must specify several optional arguments



Note: *there are many alternatives to* `data.table::fread()`*, including from* `base R` *or the* `tidyverse`*. But given its speed and flexibility I recommend to always use* `fread()` *and then transform the resulting* `data.table` *into a* `tibble` *or* `data.frame`*.*

Data import: exercise 1

- Download the zip file **`fread_expls.zip`** from the course homepage
- Extract the zip file within the folder **`data/raw/`** in your R project
- Write a script that imports the data set saved in the file **`fread_expls-1.csv`** into your session



How to use data.table::fread()

- *See also the tutorial on data import*
- The following arguments of `data.table::fread()` are often helpful:
  - `file`: the relative path to the csv file you want to read → use `here::here()`
  - `sep`: symbol that separates columns
  - `dec`: symbol used as decimal sign
  - `colClasses`: what object type should be used for the columns?
- For other widely used commands check the tutorial and do the exercises
  - But note that there are even more specification options → `help(fread)`

How to use data.table::fread()
Specify column separator

- *See also the tutorial on data import*
- The following arguments of `data.table::fread()` are often helpful:
  - `file`: the relative path to the csv file you want to read → use `here::here()`
  - `sep`: **symbol that separates columns**
  - `dec`: symbol used as decimal sign
  - `colClasses`: what object type should be used for the columns?
- For other widely used commands check the tutorial and do the exercises
  - But note that there are even more specification options → `help(fread)`

How to use data.table::fread()
Specify column separator

c_code; year; exports; unemployment
AT; 2013; 53.44; 5.34
AT; 2014; 53.39; 5.62
DE; 2013; 45.4; 5.23
DE; 2014; 45.64; 4.98

- Especially in Germany, columns are often separated via `;` instead of `,`
- We can pass a string to `sep` indicating how the columns are separated
  - In the above case: `sep = ";"`

How to use data.table::fread()
Specify column separator

- *See also the tutorial on data import*
- The following arguments of `data.table::fread()` are often helpful:
  - `file`: the relative path to the csv file you want to read → use `here::here()`
  - `sep`: symbol that separates columns
  - `dec`: **symbol used as decimal sign**
  - `colClasses`: what object type should be used for the columns?
- For other widely used commands check the tutorial and do the exercises
  - But note that there are even more specification options → `help(fread)`

How to use data.table::fread()
Specify decimal separator

```
c_code; year; exports; unemployment
AT; 2013; 53,44; 5,34
AT; 2014; 53,39; 5,62
DE; 2013; 45,4; 5,23
DE; 2014; 45,64; 4,98
```

- Again in Germany, decimal places are often separated via `,` instead of `.`
- We can pass a string to `dec` indicating how the columns are separated
  - In the above case: `dec = ","`

Exercise 2

- Write a script that imports the data set `fread_expls-2.csv` into your session such that the following `tibble` results:

```
# 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
```

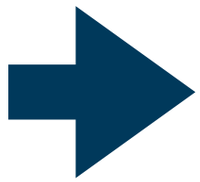
How to use data.table::fread()
Specifying column types using colClasses

- *See also the tutorial on data import*
- The following arguments of `data.table::fread()` are often helpful:
  - `file`: the relative path to the csv file you want to read → use `here::here()`
  - `sep`: symbol that separates columns
  - `dec`: symbol used as decimal sign
  - `colClasses`: **what object type should be used for the columns?**
- For other widely used commands check the tutorial and do the exercises
  - But note that there are even more specification options → `help(fread)`

How to use data.table::fread()
Specifying column types using colClasses

- Whenever numbers should be saved as character, the guessing algorithm of `data.table::fread()` often fails:

```
c_code,year,exports, PROD_CODE
AT, 2013, 53.44, 0011
AT, 2014, 53.39, 0011
DE, 2013, 45.4, 0011
DE, 2014, 45.64, 0011
```



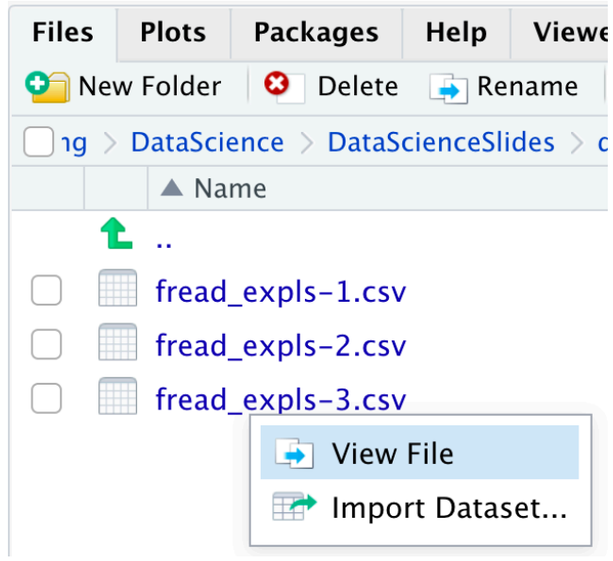
```
# A tibble: 4 × 4
  c_code  year exports PROD_CODE
  <chr>  <int>   <dbl>     <int>
1 AT      2013    53.4        11
2 AT      2014    53.4        11
3 DE      2013    45.4        11
4 DE      2014    45.6        11
```

- We can specify the column types explicitly by passing a vector to `colClasses`:
  - `colClasses = c("character", rep("double", 2), "character")`
- Usually, this is often a good idea to make your code more transparent
- You can also combine it with `select` and only read selected columns (see tutorial)

Exercise 3

- Now read in the file `fread_expls-3.csv` and use all the arguments you consider to be necessary

- Hint:
  - To get an idea about the raw data, click on the file and select “View File” to see it in its raw form → helps you to choose the right arguments:
  - Infeasible for very large files → use `nrows` and `select` to read a representative subset (see tutorial)



And what about saving data?

- Saving data is much easier than reading data
- The only relevant question is about the format
  - If there are no good arguments for using a different format, go for csv
- This can be achieved by `data.table::fwrite()` with the main arguments:
  - `x`: the name of the object to be saved
  - `file`: the file name under which the object should be saved
- Example: save object `exp_tab` to file `data/exp_tab.csv`:

```
data.table::fwrite(
    x = exp_tab,
    file = here::here("data/exp_tab.csv")
)
```

Data import - the general idea

Make yourself comfortable before reading in data - expect frustration!

- General idea: you import the data and bind it to an R object - usually a `data.frame` or whatever aligns with your preferred dialect
- Then you proceed with transforming this `data.frame` until it satisfies the demands for tidy data
- Then you save the data under a new name, save the script, and celebrate yourself 🎉🍾🥂

Summary and conclusion

- You learned how to import data into R
- Main focus: importing `csv` data files using `data.table::fread()`
  - Other **functions** for `csv` provided, e.g., via the `tidyverse` packages
  - Other **formats**: specialised functions available, esp. in the `haven` package

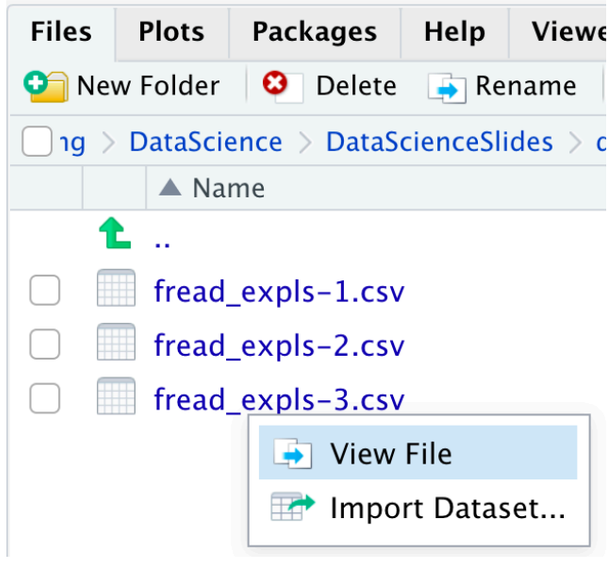
- Importing standard data often works well with **default options**
- In other cases, optional arguments must be used → check **function documentation**
- If **speed or memory restrictions** are an issue, comparing import functions is advisable

Appendix:

Typical challenges and their solution

Some general hints and suggestions I

- Always check whether the imported data set looks as expected
  - If in doubt, always look at the plain file using a plain text editor and compare!
  - Try to avoid csv data in Excel, Numbers or any other “advanced” program




```
> data_ex3 <- fread(file = data_path)
> head(data_ex3)
                cgroup commoditycode product_complexity  exp_share
                <char>         <int>              <num>      <num>
1:      Core countries           101         0.06424262 0.01312370
2: Periphery countries           101         0.06424262 0.04639794
3:      Core countries           102        -0.49254290 0.05162508
4: Periphery countries           102        -0.49254290 0.03700469
5:      Core countries           103         0.51082386 0.05324995
6: Periphery countries           103         0.51082386 0.04082251
```

```
1  cgroup,commoditycode,product_complexity,exp_share
2  Core countries,0101,0.0642426217529412,0.0131236961169874
3  Periphery countries,0101,0.0642426217529412,0.0463979373363288
4  Core countries,0102,-0.492542902941177,0.0516250772043892
5  Periphery countries,0102,-0.492542902941177,0.0370046875606996
6  Core countries,0103,0.510823855941177,0.0532499520404157
```

Some general hints and suggestions II

- **Problem**: your data set is very large an every import takes very long
- **Solution**: use `nrows=n` imports only the first `n` rows

```
data_raw <- fread(
  file = data_path, nrows = 10
)
```

- **Problem**: you are irritated by the standard data.table format of the data sets imported by `data.table::fread()`
- **Solution**: use `data.table=FALSE` to get a data.frame or use `tibble::as_tibble()` immediately

```
data_raw <- fread(
  file = data_path, data.table = FALSE
)
```

```
data_raw <- as_tibble(fread(
  file = data_path)
  )
```

Some general hints and suggestions III

- **Problem**: the column names of the imported data set are `V1, V2, …`
  - Note: this happens when the column names are numbers (e.g., years)
- **Solution**: set `header=TRUE`

```
country,Growth,year
Germany,-4.5696,2020
Germany,1.0555,2019
Germany,1.086,2018
Germany,2.6802,2017
Germany,2.23,2016
Germany,1.4919,2015
```

```
> data_raw <- as_tibble(fread(file = data_path))
> data_raw
# A tibble: 2 × 7
  V1          V2      V3      V4      V5      V6      V7
  <chr>       <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
1 country 2020    2019    2018    2017    2016    2015
2 Germany   -4.57   1.06    1.09    2.68    2.23    1.49

> data_raw <- as_tibble(fread(file = data_path, header = TRUE))
> data_raw
# A tibble: 1 × 7
  country `2020` `2019` `2018` `2017` `2016` `2015`
  <chr>    <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>
1 Germany  -4.57   1.06   1.09   2.68   2.23   1.49
```

Some general hints and suggestions IV

- **Problem**: there are one or two additional columns named `V*`
  - Note: this happens when the underlying csv file is corrupted and ends with a `,`
- **Solution**: check for the column names with `names()` and remove the corrupted columns

```
> data_raw <- as_tibble(fread(file = data_path, header = TRUE))
> data_raw
# A tibble: 1 × 5
  country `2020` `2019` `2018` V5
  <chr>    <dbl>  <dbl>  <dbl> <lgl>
1 Germany  -4.57   1.06   1.09 NA
```

```
> names(data_raw)
[1] "country" "2020"    "2019"    "2018"    "V5"
> data_raw <- select(data_raw, -all_of(c("V5")))
> data_raw
# A tibble: 1 × 4
  country `2020` `2019` `2018`
  <chr>    <dbl>  <dbl>  <dbl>
1 Germany  -4.57   1.06   1.09
```

Data preparation

The role of data preparation

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

☣ Raw data ☣ → **Data preparation and processing** → 💝 Tidy data 💝 → **Visualisation**

💝 Tidy data 💝 → **Data analysis and modelling**

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

The goal: tidy data

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

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

```
# 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 **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%)
```

- Goal of data preparation: turn such untidy data into tidy data
  - Includes data manipulation (?) and data wrangling

Short recap

- Look at the following data sets: how would a tidy version look like?

```
# A tibble: 6 × 4
  continent  year variable       value
  <fct>     <int> <chr>          <dbl>
1 Africa     2002 lifeExp         53.3
2 Africa     2002 pop        16033152.
3 Africa     2002 gdpPercap      2599.
4 Africa     2007 lifeExp         54.8
5 Africa     2007 pop        17875763.
6 Africa     2007 gdpPercap      3089.
```

```
# A tibble: 1 × 7
  country `2020` `2019` `2018` `2017` `2016` `2015`
  <chr>    <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>
1 Germany  -4.57   1.06   1.09   2.68   2.23   1.49
```

```
# A tibble: 10 × 5
   continent  year lifeExp        pop gdpPercap
   <fct>     <int>   <dbl>      <dbl>     <dbl>
 1 Africa     2002    53.3  16033152.      2599.
 2 Africa     2007    54.8  17875763.      3089.
 3 Americas   2002    72.4  33990910.      9288.
 4 Americas   2007    73.6  35954847.     11003.
 5 Asia       2002    69.2 109145521.     10174.
```

```
# A tibble: 6 × 3
  country Growth  year
  <chr>    <dbl> <int>
1 Germany  -4.57  2020
2 Germany   1.06  2019
3 Germany   1.09  2018
4 Germany   2.68  2017
5 Germany   2.23  2016
6 Germany   1.49  2015
```

Further 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?

The way to tidy data

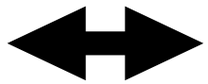
> Tidy datasets are all alike, but every messy dataset is messy in its own way.
>
> Hadley Wickham

- The starting point to tidy data is always different
  - The goal is always the same → so are the steps: **six main routines**
  - Often useful: make a physical note of how the tidy data set should look like
- 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

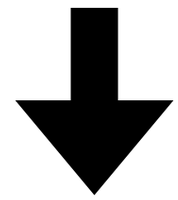
```
# A tibble: 4 × 4
  c_code  year exports unemployment
  <chr>  <int>   <dbl>        <dbl>
1 AT      2013    53.4         5.34
2 AT      2014    53.4         5.62
3 DE      2013    45.4         5.23
4 DE      2014    45.6         4.98
```

```
# 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

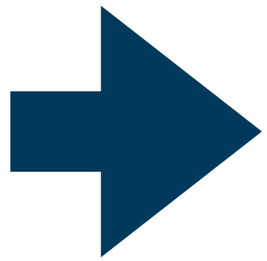
Merge several data sets

- 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

Exercises on reshaping

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

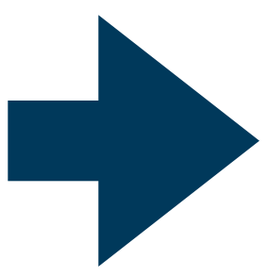
```
> data_raw_long
   country year variable    value
1: Germany 2017    unemp     3.75
2: Germany 2017      gdp 53071.46
3: Germany 2018    unemp     3.38
4: Germany 2018      gdp 53431.39
5:  Greece 2017    unemp    21.49
6:  Greece 2017      gdp 28604.86
7:  Greece 2018    unemp    19.29
8:  Greece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

Exercises 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

Source of picture: Giphy

Exercises 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.

Exercises 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`?

Source of picture: Giphy.

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

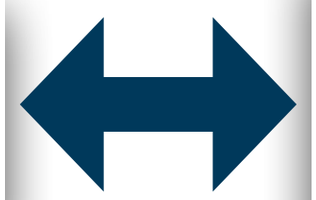
```
data_sub <- dplyr::select(
  .data = data_raw,
  country, year, unemp, gdp)
```

```
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:

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

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

```r
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?

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

- Rewrite the following code 👉 using pipes (data available via course page)

```
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

Final exercises

Final 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
```

Final 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

```
# 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()` & `dplyr::summarise()`
  - **Merging** data sets: `dplyr::*_join()`

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 👩🏼‍💻👩🏾‍💻