Working with datasets in R: A primer

Jan Vanhove

2024-06-28

Table of contents

Goal

The goal of this primer is to furnish you with the basic tools and knowledge to organise, transform, and query datasets in research contexts. We'll work with R and more specifically with the tidyverse add-on suite that markedly simplifies working with datasets.

Compiling and organising a dataset

Let's say we've run a study in which speakers of German read a couple of words in Swedish and were asked to guess what these words might mean. An excerpt from the raw data might look like this, with the words having been shown to the participants in the order in which they are listed:

- Participant 1034. Woman, 51 years.
  - Word: *söka*. Translation: *Socken* (incorrect).
  - Word: *försiktig*. Translation: *vorsichtig* (correct).
  - Word: *mjölk*. Translation: *Milch* (correct).
  - Word: *behärska*. No translation given.
  - Word: *fiende*. Translation: *finden* (incorrect).
- Participant 2384. Woman, 27 years.
  - Word: *fiende*. No translation given.
  - Word: *behärska*. No translation given.
  - Word: *försiktig*. Translation: *vorsichtig* (correct).
  - Word: *mjölk*. Translation: *Milch* (correct).
  - Word: *söka*. Translation: *Socke* (incorrect).
- Participant 8667. Woman, 27 years.
  - Word: *mjölk*. Translation: *Milch* (correct).
  - Word: *behärska*. No translation given.
  - Word: *fiende*. Translation: *finden* (incorrect).
  - Word: *söka*. Translation: *suchen* (correct).
  - Word: *försiktig*. Translation: *vorsichtig* (correct).
- Participant 5901. Man, 15 years.
  - Word: *behärska*. Translation: *beherrschen* (correct).
  - Word: *mjölk*. Translation: *milch* (sic.; correct).

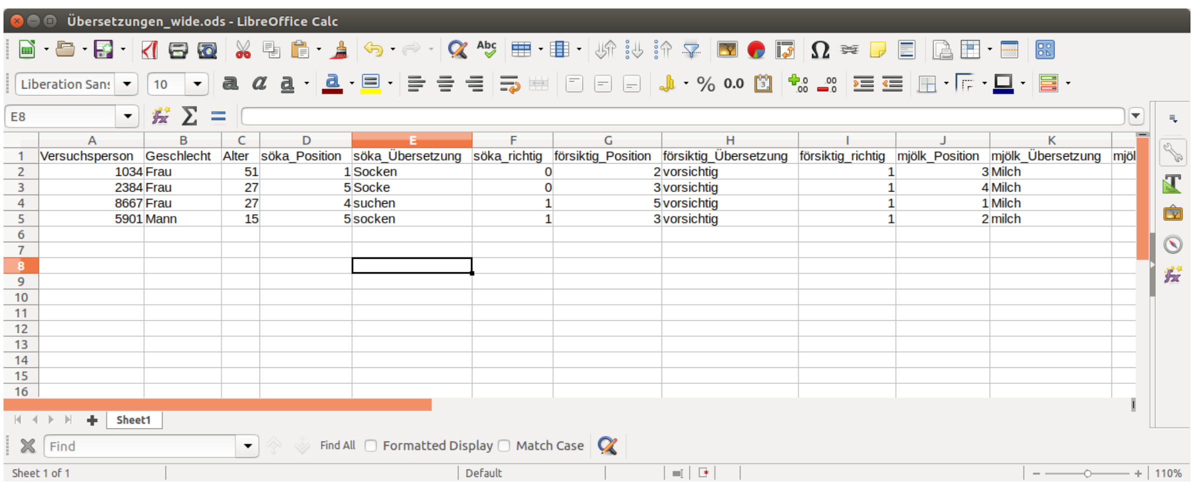
- Word: *försiktig*. Translation: *vorsichtig* (correct).
- Word: *fiende*. Translation: *feinde* (sic.; correct; actually *Feind*).
- Word: *söka*. Translation: *socken* (sic.; incorrect).

There are lots of ways in which we could represent these data in a spreadsheet. Let's look at a few rules of thumb.

Long datasets tend to be more practical than wide ones

We'll concern ourselves strictly with **rectangular** datasets. These are datasets in which the information is laid out in rows and columns and in which all columns have the same length, and all rows have the same width. Examples of non-rectangular data formats are JSON and XML – see here.

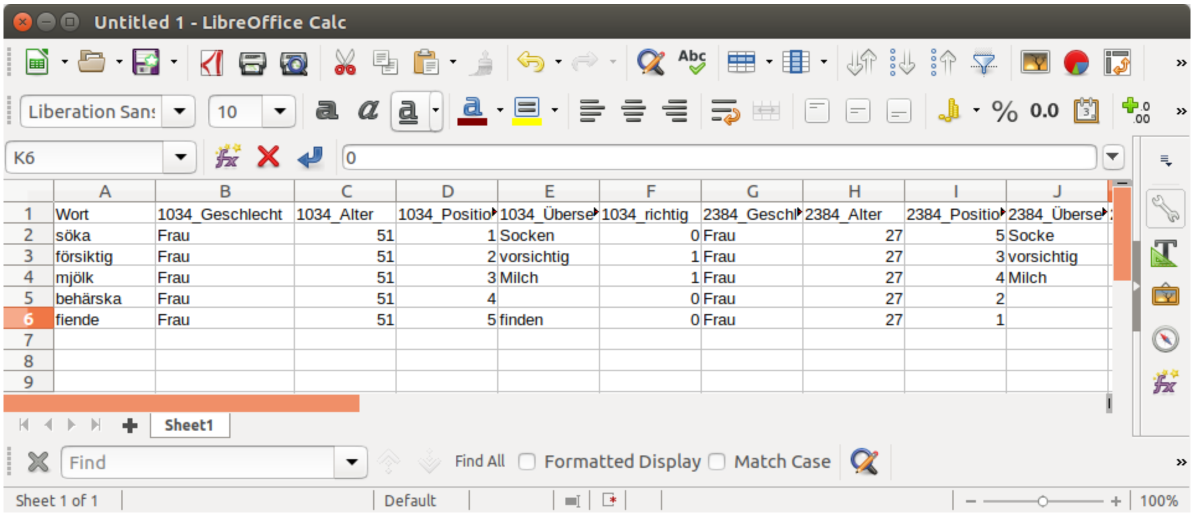
Broadly speaking, we can organise our data in a **wide** format or in a **long** format. In a **wide format**, all pieces of information related to a *unit of data collection* are organised in a single row. For instance, we could think of each participant in the study as a unit of data collection, in which case we could lay out the data as in Figure 1. Note that the spreadsheet contains a column for each word that indicates the position in which it was presented to the participants. Alternatively, we could think of each word as a unit of data collection and organise the data like in Figure 2.



Versuchsperson	Geschlecht	Alter	söka_Position	söka_Übersetzung	söka_richtig	försiktig_Position	försiktig_Übersetzung	försiktig_richtig	mjölk_Position	mjölk_Übersetzung
1034	Frau	51	1	Socken	0	2	vorsichtig	1	3	Milch
2384	Frau	27	5	Socke	0	3	vorsichtig	1	4	Milch
8667	Frau	27	4	suchen	1	5	vorsichtig	1	1	Milch
5901	Mann	15	5	socken	1	3	vorsichtig	1	2	milch

Figure 1: A wide dataset with one row per participant.

In a **long format**, all pieces of information pertaining to an *observational unit* are organised in a single row. It's difficult to precisely define what units of data collection and observational units are, and it wouldn't be too useful to have a precise definition, anyway. But in the present example, the observational units would be the individual responses, i.e., the individual translations. Figure 3 shows how the same data look like when organised in a long format.



Wort	1034_Geschlecht	1034_Alter	1034_Positio	1034_Überse	1034_richtig	2384_Geschl	2384_Alter	2384_Positio	2384_Überse
söka	Frau	51	1	Socken	0	Frau	27	5	Socke
försiktig	Frau	51	2	vorsichtig	1	Frau	27	3	vorsichtig
mjölk	Frau	51	3	Milch	1	Frau	27	4	Milch
behärska	Frau	51	4		0	Frau	27	2	
fiende	Frau	51	5	finden	0	Frau	27	1	

Figure 2: A wide dataset with one row per word.

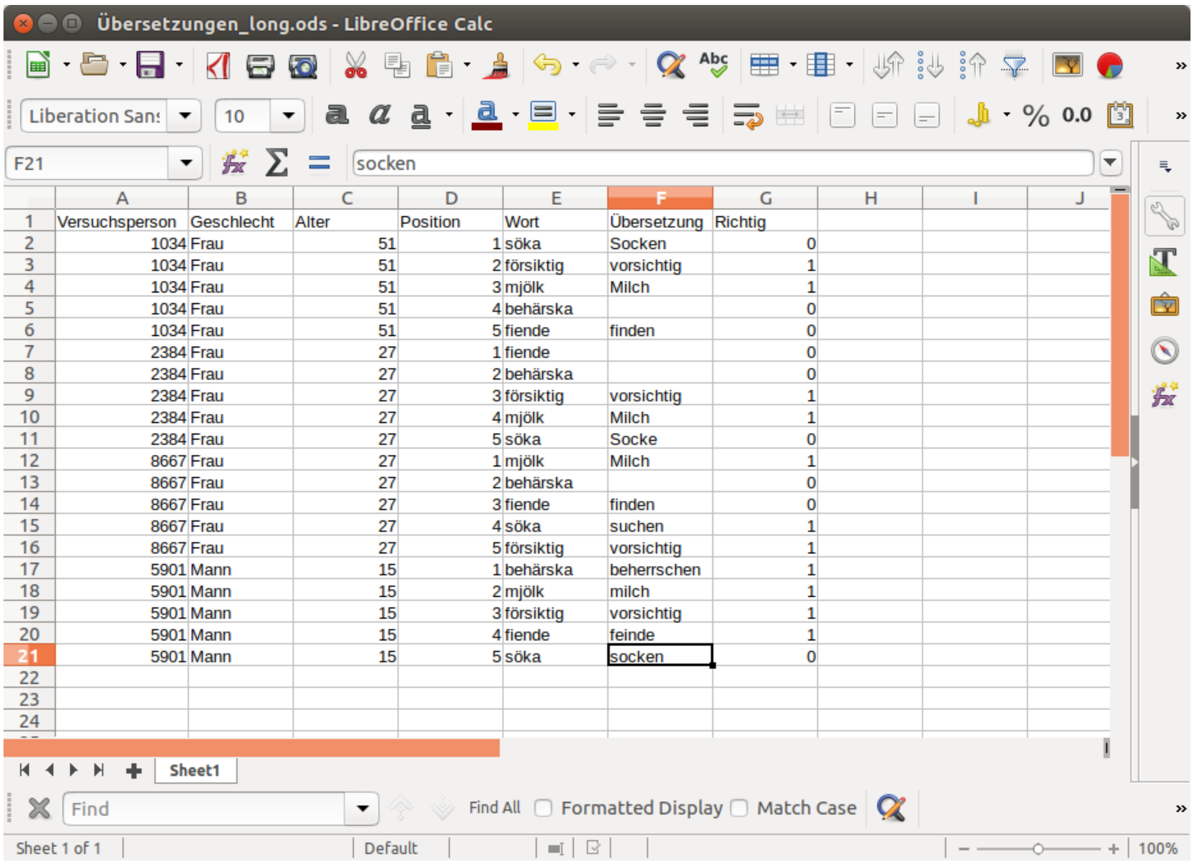
It's usually easier to work with data in a long-ish format compared to with data in a wide-ish format. Moreover, when you do need your data in a wide-ish format for data analysis, converting a longer dataset to a wider one is typically easier than vice versa. So **when in doubt** (and assuming you have a say in the matter at all), arrange your data in a **long-ish format**.

Make sure that **all rows can be interpreted independently of one another**. What we want to avoid is that we can't make sense of the data in some row because we need data from another row to do so, and this other row was deleted, or the order of the rows has changed, etc. For instance, in Figure 3, we also have a column with the `Positions`, even though we could have derived this information from the ordering of the rows. But once a row gets deleted or once the order of the rows gets permuted, we'd lose this piece of information. So don't organise the data like in Figure 4.

! Datasets are different from tables

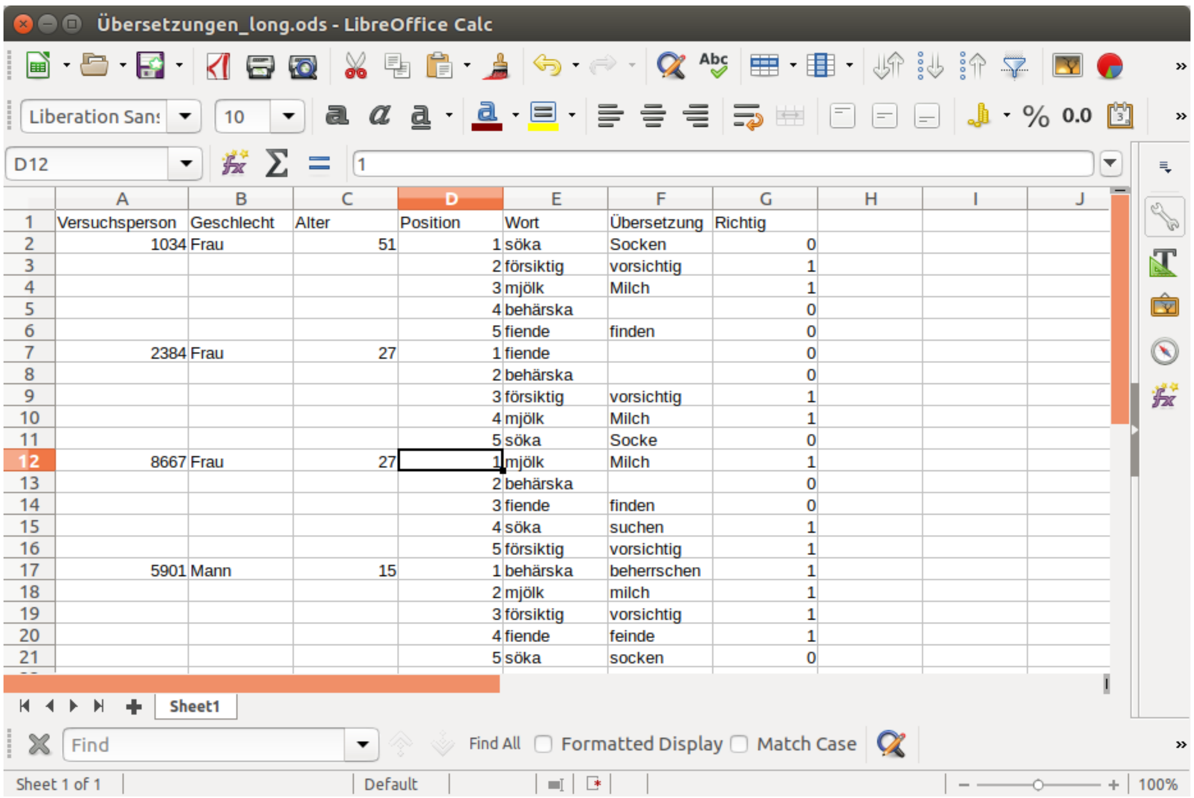
Figure 4 employs a trick often used when presenting data in a table: leave out information that didn't change compared to the last row. But the goal of a table is to *communicate* data or patterns in data, not to organise the data so that they can be analysed.

Furthermore, the dataset needs to be rectangular. Figure 5 shows what *not* to do: The additional rows reporting some averages don't fit in with the rest of the dataset ("Prozent Männer:" is not the ID of a `Versuchsperson`, and "30" is not a `Geschlecht`).



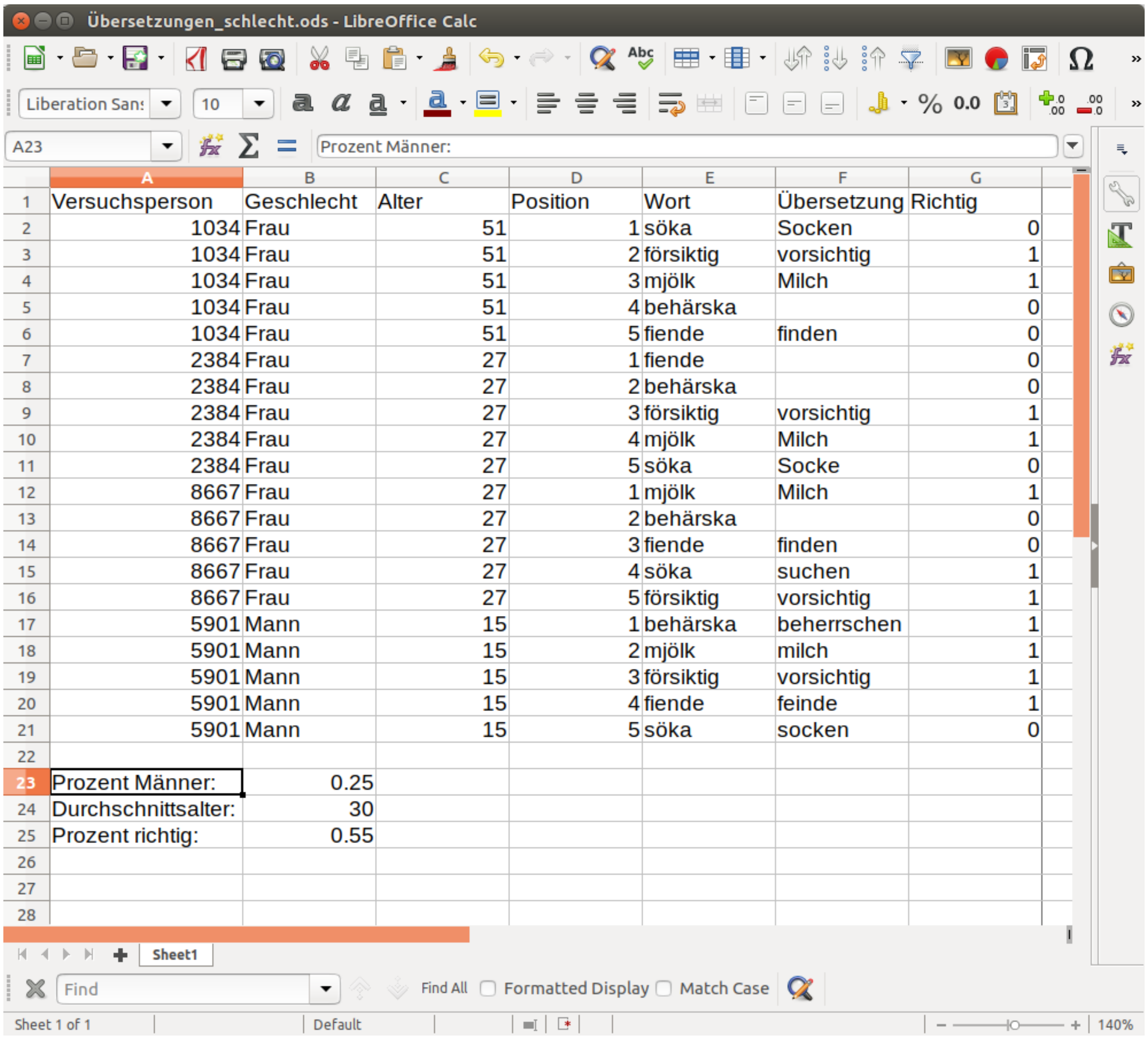
	Versuchsperson	Geschlecht	Alter	Position	Wort	Übersetzung	Richtig
2	1034	Frau	51	1	söka	Socken	0
3	1034	Frau	51	2	försiktig	vorsichtig	1
4	1034	Frau	51	3	mjölk	Milch	1
5	1034	Frau	51	4	behärska		0
6	1034	Frau	51	5	fiende	finden	0
7	2384	Frau	27	1	fiende		0
8	2384	Frau	27	2	behärska		0
9	2384	Frau	27	3	försiktig	vorsichtig	1
10	2384	Frau	27	4	mjölk	Milch	1
11	2384	Frau	27	5	söka	Socke	0
12	8667	Frau	27	1	mjölk	Milch	1
13	8667	Frau	27	2	behärska		0
14	8667	Frau	27	3	fiende	finden	0
15	8667	Frau	27	4	söka	suchen	1
16	8667	Frau	27	5	försiktig	vorsichtig	1
17	5901	Mann	15	1	behärska	beherrschen	1
18	5901	Mann	15	2	mjölk	milch	1
19	5901	Mann	15	3	försiktig	vorsichtig	1
20	5901	Mann	15	4	fiende	feinde	1
21	5901	Mann	15	5	söka	socken	0

Figure 3: A long dataset with one row per word per participant. Long datasets tend to be easier to manage and to analyse than wide ones.



	A	B	C	D	E	F	G
1	Versuchsperson	Geschlecht	Alter	Position	Wort	Übersetzung	Richtig
2	1034	Frau	51	1	söka	Socken	0
3				2	försiktig	vorsichtig	1
4				3	mjölk	Milch	1
5				4	behärska		0
6				5	fiende	finden	0
7	2384	Frau	27	1	fiende		0
8				2	behärska		0
9				3	försiktig	vorsichtig	1
10				4	mjölk	Milch	1
11				5	söka	Socke	0
12	8667	Frau	27	1	mjölk	Milch	1
13				2	behärska		0
14				3	fiende	finden	0
15				4	söka	suchen	1
16				5	försiktig	vorsichtig	1
17	5901	Mann	15	1	behärska	beherrschen	1
18				2	mjölk	milch	1
19				3	försiktig	vorsichtig	1
20				4	fiende	feinde	1
21				5	söka	socken	0

Figure 4: Not like this! In this dataset, several cells are left empty as their contents can be derived from other cells. But this will result in difficulties when analysing the data. Moreover, deleting some rows or changing their order would make it impossible to reconstruct the intended contents of these empty cells.



	A	B	C	D	E	F	G
1	Versuchsperson	Geschlecht	Alter	Position	Wort	Übersetzung	Richtig
2	1034	Frau	51	1	söka	Socken	0
3	1034	Frau	51	2	försiktig	vorsichtig	1
4	1034	Frau	51	3	mjölk	Milch	1
5	1034	Frau	51	4	behärska		0
6	1034	Frau	51	5	fiende	finden	0
7	2384	Frau	27	1	fiende		0
8	2384	Frau	27	2	behärska		0
9	2384	Frau	27	3	försiktig	vorsichtig	1
10	2384	Frau	27	4	mjölk	Milch	1
11	2384	Frau	27	5	söka	Socke	0
12	8667	Frau	27	1	mjölk	Milch	1
13	8667	Frau	27	2	behärska		0
14	8667	Frau	27	3	fiende	finden	0
15	8667	Frau	27	4	söka	suchen	1
16	8667	Frau	27	5	försiktig	vorsichtig	1
17	5901	Mann	15	1	behärska	beherrschen	1
18	5901	Mann	15	2	mjölk	milch	1
19	5901	Mann	15	3	försiktig	vorsichtig	1
20	5901	Mann	15	4	fiende	feinde	1
21	5901	Mann	15	5	söka	socken	0
22							
23	Prozent Männer:	0.25					
24	Durchschnittsalter:	30					
25	Prozent richtig:	0.55					
26							
27							
28							

Figure 5: Not like this! This dataset is not rectangular.

Use short but descriptive variable names

Make your life during the data analysis easier by using short but descriptive labels for variables or values in the spreadsheet. By doing so, you avoid that you constantly need to look up in the project's codebook what the labels mean, thereby reducing the likelihood that you'll make errors. Moreover, you save yourself some typing.

A few examples:

- When working with questionnaire data, don't simply label the columns with the number of the question in the questionnaire (e.g., `Q3` or `Question17`). Instead, use more descriptive labels such as `DegreeFather` oder `DialectUse`.
- If you have a column labelled `Sex` that is filled with 1s and 0s, then you may end up having to look up if the 1s refer to men or to women. Instead, either fill the column with `m(an)` and `w(oman)` values, or rename the column `Man`, so that you know that the 1s refer to men.
- Try to strike a balance between descriptive power and length. For instance, a variable named `HowOftenDoYouSpeakStandardGerman` will get on your nerves before long; `SpeakStandard` could be sufficient.

> **!** Use a codebook
>
> Having short and descriptive variable names is not an excuse for not maintaining a codebook that spells out precisely what each variable in the dataset refers to. [Example of a codebook].

Label missing values unambiguously

In Figure 3, I left some of the translation cells empty. From this, I can deduce that the word was presented to the participant but that he or she did not translate the word. However, it could have been possible that some participants were inadvertently never shown a particular word (e.g., due to a programming error) or that some of the participants' were irretrievably lost. We should enable ourselves to distinguish between these cases, for instance by marking the latter cases using `NA` (*not available*).

If you want to be able to tell apart different reasons for missing data (such as data loss, programming errors, participants' refusal to answer a certain question, participants' being absent from a data collection etc.), it's probably easiest to just write `NA` in the column and add another column with comments detailing the reasons for the missingness.

Don't use numbers to encode missingness

Some data logging applications use -99 or -9999 to encode missingness. The problem with this is that, sometimes, -99 or -9999 don't immediately stand out as conspicuous values.

Reduce redundancy by splitting up datasets

The spreadsheet above contain several repeated pieces of information. For instance, for all five translations provided by participant 1034, we indicated that they were provided by a woman aged 51. We can eliminate this source of redundancy by managing a handful of smaller datasets rather than just a single large one. More specifically, we can manage a dataset that contains all information that depends *just* on the participants, see Figure 6. Each participant has a unique ID (here: `Versuchsperson`), and the dataset contains contains a single row for each participant. If we need to correct an entry related to, say, some participant's age, we just need to change it here – once – rather than five times in the larger dataset.

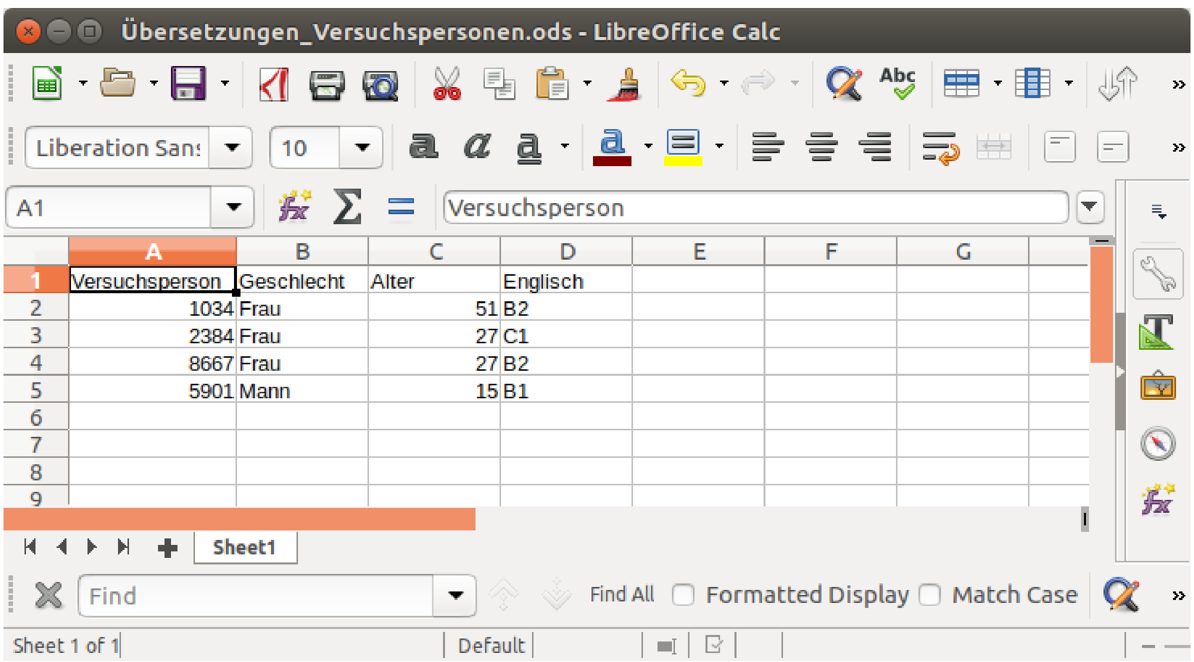


Figure 6: The first smaller dataset only contains information concerning the participants.

By the same token, we can put all information that depends *just* on the stimuli used in a separate dataset, see Figure 7. Here, too, each stimulus has a unique ID (here: `Wort`).

The third dataset then only contains information that depends on the *combination* of a particular participant and a particular word. As shown in Figure 8, each row in this dataset contains

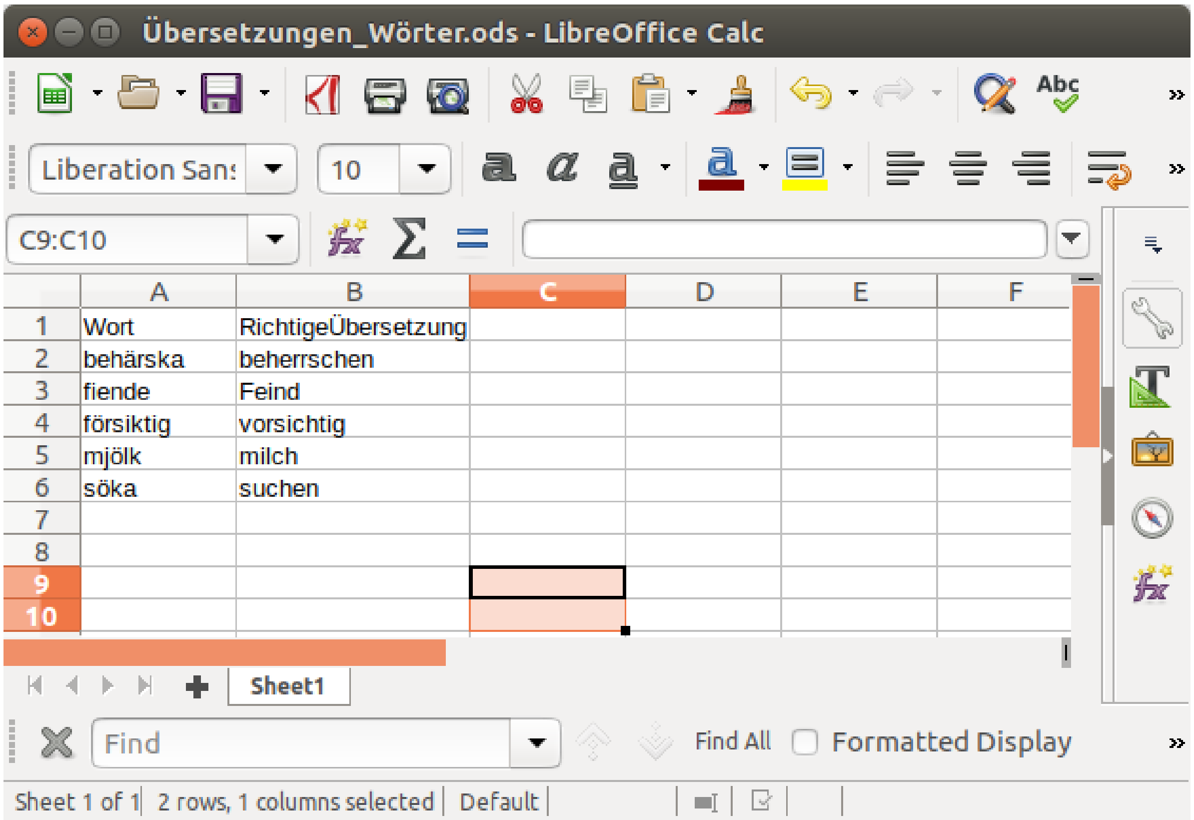


Figure 7: The second smaller dataset only contains information concerning the words.

the IDs of both the participant and the stimulus that the response is related to. But any other information related to just the word or to just the participant is left out of this dataset. As we'll see shortly, we can easily add the information related to the participants or to the words to this dataset from the other two datasets.

Miscellaneous tips

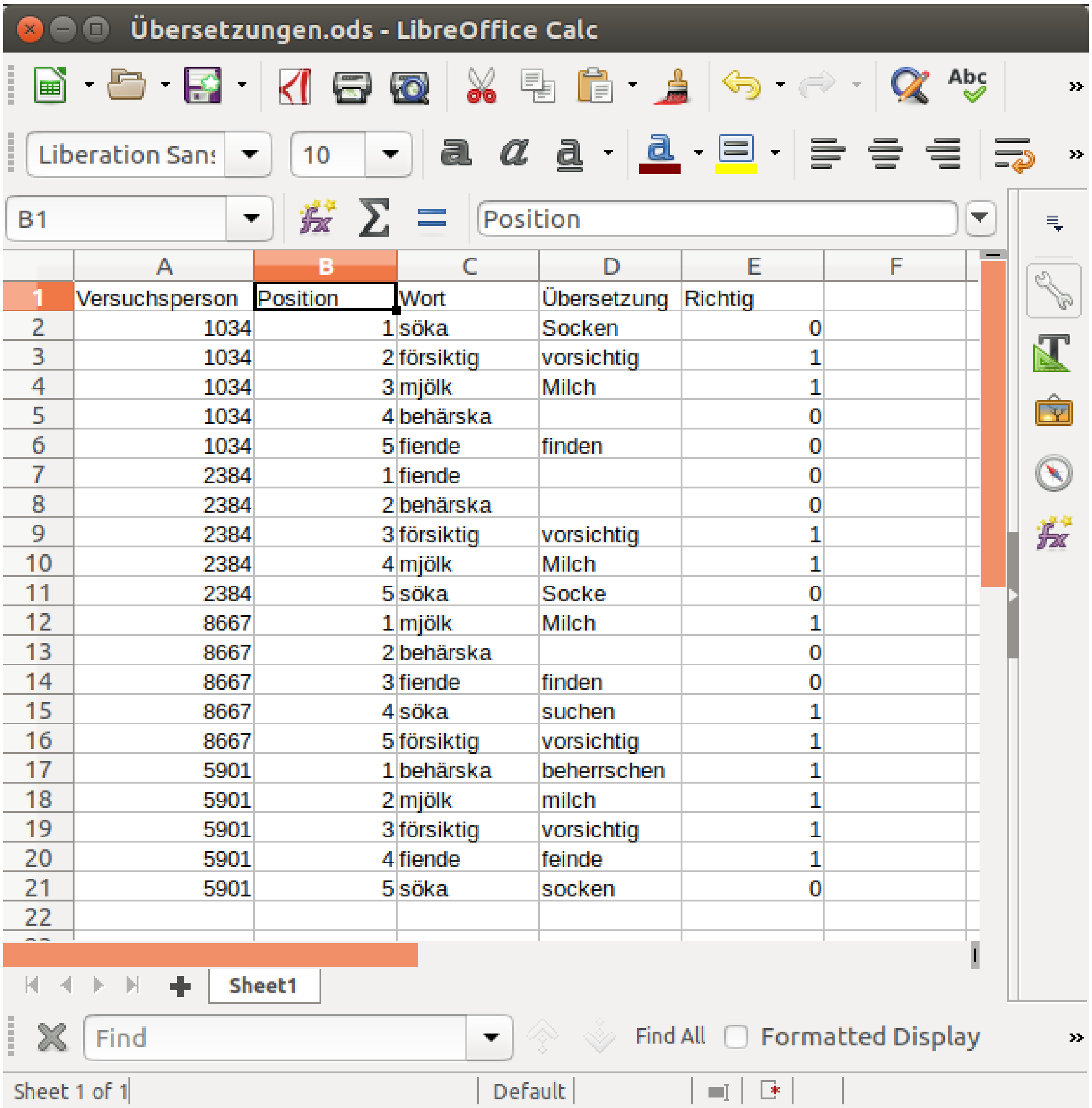
- Mind capitalisation. For some programs and computer languages, `Frau` and `frau` are the same value; for others (including R), they are not.
- Mind trailing spaces. "Mann " (with trailing space) and "Mann" (without trailing space) are different values to a computer.
- Special symbols, including the Umlaut, sometimes lead to problems, especially when collaborating with people whose localisation settings differ from yours.
- Format dates in the YYYY/MM/DD format. This way, if you sort the data alphabetically, they're already in chronological order.
- Don't use colour-coding in your spreadsheet. Or if you do use it, be aware that you'll lose this information once you import your data into your statistics program.

Work as little as possible in the spreadsheet

After you've entered your data into a spreadsheet, all further steps in your analysis should be carried out in R (or Python, or Julia, or what-have-you). Don't calculate, sort, copy, paste, move, reshape, draw graphs etc. in Excel or whatever spreadsheet program you prefer. Treat your finished spreadsheet as the **immutable** source of data from which your results will be obtained, so that when in doubt, it's clear which file you should go back to.
When using R (or Python, or Julia, or whatever), use (a) script(s) to read in the original dataset and convert the data in it to a format more amenable to analysis, but whatever you do, don't overwrite the original file.

Use data validation

When working in a spreadsheet program, you can use the data validation functions to minimise the chances that you enter faulty data. For instance, if you know that the possible responses to a certain questions are either integers from 0 to 5 or `NA`, make a data validation rule that prevents you from entering erroneous data.
Also see the blog post *A data entry form with failsafes*.



Versuchsperson	Position	Wort	Übersetzung	Richtig
1034	1	söka	Socken	0
1034	2	försiktig	vorsichtig	1
1034	3	mjölk	Milch	1
1034	4	behärska		0
1034	5	fiende	finden	0
2384	1	fiende		0
2384	2	behärska		0
2384	3	försiktig	vorsichtig	1
2384	4	mjölk	Milch	1
2384	5	söka	Socke	0
8667	1	mjölk	Milch	1
8667	2	behärska		0
8667	3	fiende	finden	0
8667	4	söka	suchen	1
8667	5	försiktig	vorsichtig	1
5901	1	behärska	beherrschen	1
5901	2	mjölk	milch	1
5901	3	försiktig	vorsichtig	1
5901	4	fiende	feinde	1
5901	5	söka	socken	0

Figure 8: The third dataset only contains the translations.

Working with R and RStudio

With the data available in a rectangular spreadsheet format, the next challenge is to load them into a program capable of analysing them. Several (free) options are available (JASP, Python, Julia, …), but we'll focus on R complemented with the `tidyverse` suite. The main reasons for this are that R is more popular in the humanities and the social sciences and that I'm just more proficient in R. Hadley Wickham lists some further reasons.

R, RStudio, and the tidyverse

To install R, visit the R Project website.

In addition, I recommend you install RStudio, which facilitates working with R. To do so, visit the Posit website and download the open source desktop version of RStudio.

Once you've installed R and RStudio, open RStudio, and go to `Tools > Global options...`. In the tab `General, Basic`, make sure to *untick* the option 'Restore .RData into workspace at startup' and select the option 'never' for 'Save workspace to .RData on exit'. These settings help ensure that you're starting from a clean slate each time you open RStudio and prevent the results of calculations in previous sessions from messing up your analyses. Additionally, in the tab `Code, Editing`, tick the box next to 'Use native pipe operator, |>'. We'll encounter this pipe operator shortly. Finally, I recommend setting the default text encoding to UTF-8 (`Code, Saving`).

The functionality of R can be extended by installing further packages. We'll be using two of these. The first is the `here` package, which makes it easier to read in data files if you're working in a complex file system. Nothing in what follows hinges on your using the `here` package or not; I just find that it makes my life easier. To install the `here` package, type the following command at the R prompt:

```r
install.packages("here")
```

The second package isn't optional if you want to following along with the rest of this course: The `tidyverse` actually bundles a couple of package that are based on a set of shared principles and that facilitate working with datasets enormously. You can install it like so:

```r
install.packages("tidyverse")
```

Setting up an R project

Next, in RStudio, click on `File > New Project... > New Directory`. Navigate to somewhere on your computer where you want to create a new directory and give this directory a name (for instance, `DatasetsAndGraphs`). You will use this directory to store the data and scripts that you'll need for drawing the graphs in as well for saving the graphs themselves to. You don't have to tick the other options.

When you're done, close RStudio. Navigate to the directory you've just created. You should find an `.Rproj` file there. Double-click it. If all is well, RStudio should fire up.

Create the following subdirectories in the directory you're currently in: `data`, `scripts` and `figs`.

On github.com/janhove/DatasetsAndGraphs, you can find a couple of datasets (under `data`) as well as an R script that defines a new function we'll use (under `functions`). Put the datasets in your own `data` directory and the R script in your own `functions` directory.

You've now set up an R project for this pair of lectures. R projects aren't strictly necessary, but I find them helpful to manage different research projects, publications, classes I teach.

Loading the packages

We'll work with the `here` and `tidyverse` packages below. Even if you've already installed these, you need to *load* these packages in every R session in which you use them. To do so, execute the following lines:

```
library(here)
```

```
here() starts at C:/Users/VanhoveJ/switchdrive/Documents/Workshops/DatasetsAndGraphs
```

```
library(tidyverse)
```

```
-- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
v dplyr     1.1.4     v readr     2.1.5
v forcats   1.0.0     v stringr   1.5.1
v ggplot2   3.5.1     v tibble    3.2.1
v lubridate 1.9.3     v tidyr     1.3.1
v purrr     1.0.2

-- Conflicts ------------------------------------------ tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
x dplyr::lag()    masks stats::lag()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to becom
```

Incidentally, you don't need to install these packages every time you need them, but you do need to load them every time you need them in a new session. I recommend including the packages you need at the top of your script.

> **Use scripts**
>
> With few exceptions, you should type the commands you want to execute in an R script (`File > New File > R Script`) rather than directly in the R console. While nothing terrible will happen if you do enter commands directly into the console, entering them into the script editor first is a good habit to get into: it's much easier to spot errors, save *and* document your analysis, make tweaks to your code, and reuse old code in the editor than in the console.
> As a rule of thumb, for the analysis of large projects, I tend to create separate R scripts for different parts of the analysis that are internally closely connected but more or less independent of the other parts. For instance, I might have a script for cleaning the datasets, another script for the analyses that are reported in Chapter 4, and yet another script for the analyses reported in Chapter 5.

Reading in datasets

Excel files

We'll focus on reading in two kinds of spreadsheets: Excel spreadsheets in the XLS(X) format, and CSV files.

In order to read in XLS(X) files, we need the `readxl` package. This package is part of the `tidyverse` suite, but it does not get loaded automatically as you load the `tidyverse` suite. So we load it separately:

```
library(readxl)
```

Assuming the file `uebersetzungen.xlsx` is located in the `data` subdirectory of your R project directory, we can read it into R as follows.

```
translations <- read_excel(here("data", "uebersetzungen.xlsx"))
```

The dataset is now loaded as a so-called *tibble* named `translations`. We can display it by simply typing its name at the prompt:

```
translations
```

```
# A tibble: 20 x 5
   Versuchsperson Position Wort      Übersetzung Richtig
            <dbl>    <dbl> <chr>     <chr>         <dbl>
 1           1034        1 söka      Socken            0
 2           1034        2 försiktig vorsichtig        1
 3           1034        3 mjölk     Milch             1
 4           1034        4 behärska  <NA>              0
 5           1034        5 fiende    finden            0
 6           2384        1 fiende    <NA>              0
 7           2384        2 behärska  <NA>              0
 8           2384        3 försiktig vorsichtig        1
 9           2384        4 mjölk     Milch             1
10           2384        5 söka      Socke             0
11           8667        1 mjölk     Milch             1
12           8667        2 behärska  <NA>              0
13           8667        3 fiende    finden            0
14           8667        4 söka      suchen            1
15           8667        5 försiktig vorsichtig        1
16           5901        1 behärska  beherrschen       1
17           5901        2 mjölk     milch             1
18           5901        3 försiktig vorsichtig        1
19           5901        4 fiende    feinde            1
20           5901        5 söka      socken            0
```

Type, don't copy-paste – at home

You're going to take away much more from this primer if you copy the code snippets by *typing* them rather than by copy-pasting them. That said, I strongly advise you to do so in your own time and not as you're attending the lecture: Some things are bound to go wrong (perhaps a comma in the wrong spot, a missing bracket or an upper-case letter that should have been a lower-case one), and as you're trying to fix the errors, you'll lose track of the lecture.
So work through the code snippets at home, and be patient with yourselves. I receive error messages or unexpected outcomes all the time – it's just that after using R for 15 or so years, I've become reasonably proficient at spotting the problems and Googling solutions :)

Data frames and tibbles

Rectangular data sets are referred to as *data frames* in R. The `tidyverse` slightly changes their functionality, mostly in order to allow for prettier displaying, and refers to them as *tibbles*.

> **Empty strings interpreted as missing**
>
> Note that the empty cells are automatically interpreted as missing data (`<NA>`). The documentation of the `read_excel()` function, which you can access by typing `?read_excel` at the R prompt, suggests that we can override this behaviour, but we can't.

If, instead of printing the entire tibble at the prompt, we just want to display the first few rows, we can use `slide_head()`:

```
slice_head(translations, n = 4)
```

```
# A tibble: 4 x 5
  Versuchsperson Position Wort      Übersetzung Richtig
           <dbl>    <dbl> <chr>     <chr>         <dbl>
1           1034        1 söka      Socken            0
2           1034        2 försiktig vorsichtig        1
3           1034        3 mjölk     Milch             1
4           1034        4 behärska  <NA>              0
```

`slice_tail()` works similarly. If you want to display a random selection of rows, you can use `slice_sample()`:

```
slice_sample(translations, n = 5)
```

```
# A tibble: 5 x 5
  Versuchsperson Position Wort      Übersetzung Richtig
           <dbl>    <dbl> <chr>     <chr>         <dbl>
1           5901        2 mjölk     milch             1
2           2384        2 behärska  <NA>              0
3           1034        2 försiktig vorsichtig        1
4           1034        4 behärska  <NA>              0
5           5901        3 försiktig vorsichtig        1
```

Again, for details, you can check the documentation of these functions that is available at `?slice_head`.

CSV files

A popular format for storing spreadsheets is the CSV format. CSV is short for *comma-separated values*: Cells on the same row are separated by commas, see Figure 9. Sometimes, text strings are additionally surrounded by quotation marks.

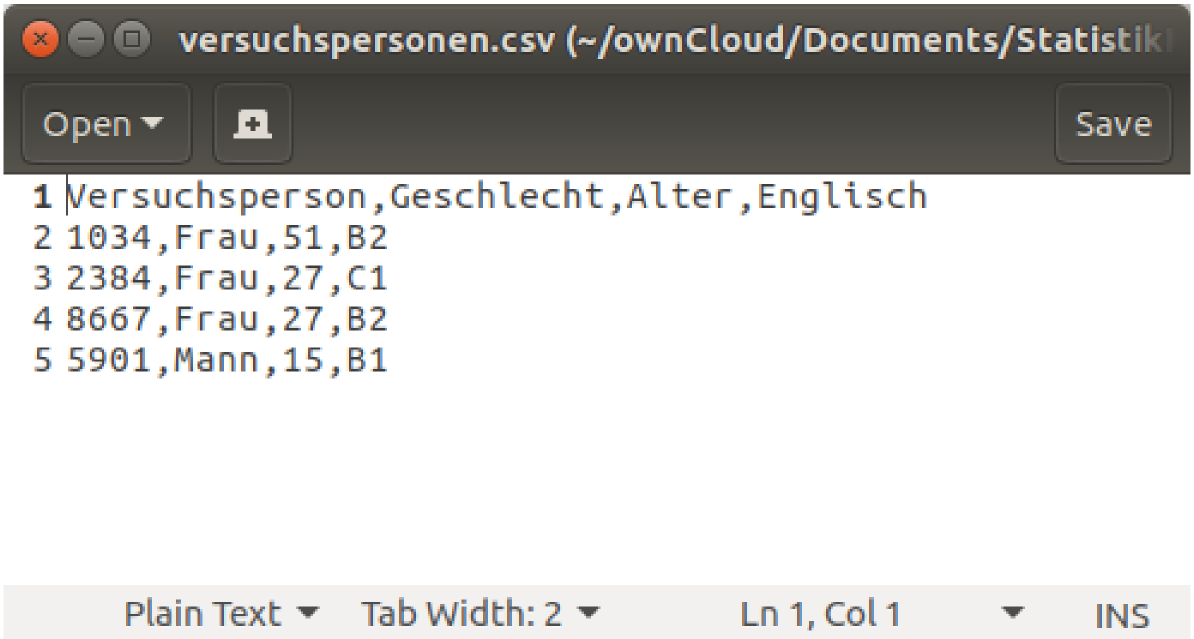


Figure 9: A spreadsheet stored as *comma-separated values.*

To read in CSV files, we can use the `read_csv()` function, which is part of the `readr` package, which in turn is automatically loaded when the `tidyverse` suit is loaded:

```r
translations <- read_csv(here("data", "uebersetzungen.csv"))
```

```
Rows: 20 Columns: 5
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (2): Wort, Übersetzung
dbl (3): Versuchsperson, Position, Richtig

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
translations
```

```
# A tibble: 20 x 5
   Versuchsperson Position Wort      Übersetzung Richtig
            <dbl>    <dbl> <chr>     <chr>         <dbl>
 1           1034        1 söka      Socken            0
```

```
2             1034          2 försiktig vorsichtig         1
3             1034          3 mjölk     Milch              1
4             1034          4 behärska  <NA>               0
5             1034          5 fiende    finden             0
6             2384          1 fiende    <NA>               0
7             2384          2 behärska  <NA>               0
8             2384          3 försiktig vorsichtig         1
9             2384          4 mjölk     Milch              1
10            2384          5 söka      Socke              0
11            8667          1 mjölk     Milch              1
12            8667          2 behärska  <NA>               0
13            8667          3 fiende    finden             0
14            8667          4 söka      suchen             1
15            8667          5 försiktig vorsichtig         1
16            5901          1 behärska  beherrschen        1
17            5901          2 mjölk     milch              1
18            5901          3 försiktig vorsichtig         1
19            5901          4 fiende    feinde             1
20            5901          5 söka      socken             0
```

We receive a couple of messages (not errors!). These show that the `read_csv()` function correctly recognised that the columns `Wort` and `Übersetzung` contain text ('chr', character) strings, whereas `Versuchsperson`, `Position` and `Richtig` contain numbers ('dbl' for 'double', a number format).

> **Empty strings interpreted as missing**
>
> With `read_csv()`, we can specify that only cells containing "NA" are marked as missing data:
>
> ```
> translations2 <- read_csv(here("data", "uebersetzungen.csv"), na = "NA")
> ```
>
> ```
> Rows: 20 Columns: 5
> -- Column specification --------------------------------------------------------
> Delimiter: ","
> chr (2): Wort, Übersetzung
> dbl (3): Versuchsperson, Position, Richtig
>
> i Use `spec()` to retrieve the full column specification for this data.
> i Specify the column types or set `show_col_types = FALSE` to quiet this message.
> ```
>
> ```
> translations2
> ```

```
# A tibble: 20 x 5
   Versuchsperson Position Wort      Übersetzung   Richtig
            <dbl>    <dbl> <chr>     <chr>           <dbl>
 1           1034        1 söka      "Socken"            0
 2           1034        2 försiktig "vorsichtig"        1
 3           1034        3 mjölk     "Milch"             1
 4           1034        4 behärska  ""                  0
 5           1034        5 fiende    "finden"            0
 6           2384        1 fiende    ""                  0
 7           2384        2 behärska  ""                  0
 8           2384        3 försiktig "vorsichtig"        1
 9           2384        4 mjölk     "Milch"             1
10           2384        5 söka      "Socke"             0
11           8667        1 mjölk     "Milch"             1
12           8667        2 behärska  ""                  0
13           8667        3 fiende    "finden"            0
14           8667        4 söka      "suchen"            1
15           8667        5 försiktig "vorsichtig"        1
16           5901        1 behärska  "beherrschen"       1
17           5901        2 mjölk     "milch"             1
18           5901        3 försiktig "vorsichtig"        1
19           5901        4 fiende    "feinde"            1
20           5901        5 söka      "socken"            0
```

Note that the `Übersetzung` value in row 4 is just empty, not `NA`.

Let's also read in the datasets containing the information pertaining to the participants and items:

```
participants <- read_csv(here("data", "versuchspersonen.csv"))
```

```
Rows: 4 Columns: 4
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (2): Geschlecht, Englisch
dbl (2): Versuchsperson, Alter

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
items <- read_csv(here("data", "woerter.csv"))
```

```
Rows: 5 Columns: 2
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (2): Wort, RichtigeÜbersetzung

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

> **Different CSV formats**
>
> If you save an Excel spreadsheet as a CSV file on a French- or German-language computer system, the cells will be separated using semicolons rather than using commas. The reason is that commas are used as decimal separators in French and German. To read in 'CSV' files that use semicolons as cell separators, you can use the `read_csv2()` function. Incidentally, if you use LibreOffice.org Calc instead of Excel, you can choose which cell separator gets used if you export a spreadsheet as a CSV file.

> **`read_csv()` vs. `read.csv()`**
>
> More seasoned R users are probably already familiar with the `read.csv()` function (with a dot rather than an underscore). The `read_csv()` function is merely the `tidyverse` counterpart to this function. The practical differences between them are negligible.

Other formats

For reading in data from Google Sheets, see googlesheets4.

For interacting with Google Drive, see googledrive.

For reading in SPSS, Stata and SAS files, see haven.

Joining datasets

Having read in our three datasets as `translations`, `participants`, and `items`, we want to merge these datasets into one large dataset. The most useful function for this is `left_join()`, which takes the dataset passed as its `x` argument and adds to this the corresponding rows from the `y` dataset:

```r
all_data <- left_join(x = translations, y = participants)
```

```
Joining with `by = join_by(Versuchsperson)`
```

Note that the `left_join()` function recognises that the variable shared between both datasets is called `Versuchsperson`. Hence, the information related to participant 1034 contained in `participants` is added to each row in `translations` where the `Versuchsperson` value is 1034, and similarly for the other participants:

```
all_data
```

```
# A tibble: 20 x 8
   Versuchsperson Position Wort    Übersetzung Richtig Geschlecht Alter Englisch
            <dbl>    <dbl> <chr>   <chr>         <dbl> <chr>      <dbl> <chr>
 1           1034        1 söka    Socken            0 Frau          51 B2
 2           1034        2 försik~ vorsichtig        1 Frau          51 B2
 3           1034        3 mjölk   Milch             1 Frau          51 B2
 4           1034        4 behärs~ <NA>              0 Frau          51 B2
 5           1034        5 fiende  finden            0 Frau          51 B2
 6           2384        1 fiende  <NA>              0 Frau          27 C1
 7           2384        2 behärs~ <NA>              0 Frau          27 C1
 8           2384        3 försik~ vorsichtig        1 Frau          27 C1
 9           2384        4 mjölk   Milch             1 Frau          27 C1
10           2384        5 söka    Socke             0 Frau          27 C1
11           8667        1 mjölk   Milch             1 Frau          27 B2
12           8667        2 behärs~ <NA>              0 Frau          27 B2
13           8667        3 fiende  finden            0 Frau          27 B2
14           8667        4 söka    suchen            1 Frau          27 B2
15           8667        5 försik~ vorsichtig        1 Frau          27 B2
16           5901        1 behärs~ beherrschen       1 Mann          15 B1
17           5901        2 mjölk   milch             1 Mann          15 B1
18           5901        3 försik~ vorsichtig        1 Mann          15 B1
19           5901        4 fiende  feinde            1 Mann          15 B1
20           5901        5 söka    socken            0 Mann          15 B1
```

If you don't want the `left_join()` function to figure out what the shared variable is, you can specify it explicitly:

```
all_data <- left_join(x = translations, y = participants, by = "Versuchsperson")
```

If the shared variable has different names in the different datasets, you can use something like

```
new <- left_join(x = left_dataset, y = right_dataset, by = join_by(var_left == var_right))
```

See `?join_by` for more information.

If there are values in the shared variable that occur in the `x` dataset that don't occur in the `y` dataset, the values in the added columns will read `NA` for these rows.

Further join functions are the following, see `?join` for details:

- `right_join(x, y)`: Keep all entries in `y`. Add corresponding entries in `x` to it.
- `full_join(x, y)`: Keep all entries in both `x` and `y`. Add `NA`s if there is no corresponding entry in the other dataset.
- `inner_join(x, y)`: Only keep entries in `x` for which there is a corresponding entry in `y`. Add these corresponding entries.
- `semi_join(x, y)`: Only keep entries in `x` for which there is a corresponding entry in `y`. Don't add these corresponding entries.
- `anti_join(x, y)`: Only keep entries in `x` for which there are *no* corresponding entries in `y`.

In the current example, `left_join`, `full_join` and `inner_join` would all yield the same result. But this isn't always the case.

Let's also add the information pertaining to the words:

```
all_data <- left_join(all_data, items)
```

```
Joining with `by = join_by(Wort)`
```

Incidentally, another way of achieving the same result is this:

```
all_data <- translations |>
  left_join(participants) |>
  left_join(items)
```

```
Joining with `by = join_by(Versuchsperson)`
Joining with `by = join_by(Wort)`
```

Exercise: join functions

1. Use the following code to generate two tibbles called `left` and `right`:

```
left <- tibble(A = c("a", "b", "c", NA),
               B = c(1, 2, NA, 4))
right <- tibble(B = c(1, 3, 4, 4),
                C = c(10, NA, 12, 7))
left
```

```
# A tibble: 4 x 2
  A         B
  <chr> <dbl>
1 a         1
2 b         2
3 c        NA
4 <NA>      4
```

```r
right
```

```
# A tibble: 4 x 2
      B     C
  <dbl> <dbl>
1     1    10
2     3    NA
3     4    12
4     4     7
```

2. *Without running these commands*, predict what their output would look like:

```r
left_join(x = left, y = right)
right_join(x = left, y = right)
full_join(x = left, y = right)
inner_join(x = left, y = right)
semi_join(x = left, y = right)
semi_join(x = recht, y = left) # !
anti_join(x = left, y = right)
anti_join(x = right, y = left) # !
```

3. Now run the commands above to verify your predictions.

4. Create two new tibbles using the code below:

```r
left <- tibble(A = c("a", "b"),
               B = c(1, NA))
right <- tibble(B = c(1, NA, NA),
                C = c(0, 1, 2))
left
```

```
# A tibble: 2 x 2
  A         B
```

```
  <chr> <dbl>
1 a         1
2 b        NA
```

```
right
```

```
# A tibble: 3 x 2
      B     C
  <dbl> <dbl>
1     1     0
2    NA     1
3    NA     2
```

5. Consult the help page for `left_join` and look up the `na_matches` parameter under 'Arguments'. Predict what the output of the following two commands would look like, and only then check your answer.

```
left_join(left, right)
left_join(left, right, na_matches = "never")
```

Queries

Selecting by row number

We can select the third row of a dataset like so:

```
slice(all_data, 3)
```

```
# A tibble: 1 x 9
  Versuchsperson Position Wort  Übersetzung Richtig Geschlecht Alter Englisch
           <dbl>    <dbl> <chr> <chr>         <dbl> <chr>      <dbl> <chr>
1           1034        3 mjölk Milch             1 Frau          51 B2
# i 1 more variable: RichtigeÜbersetzung <chr>
```

Alternatively, we can write this command as follows. The symbols `|>` allow us to take an object (here: `all_data`) and pass it to a function as its first argument. As we'll later see, we can use `|>` to string together a host of function calls without creating illegible code.

```r
all_data |>
  slice(3)
```

```
# A tibble: 1 x 9
  Versuchsperson Position Wort  Übersetzung Richtig Geschlecht Alter Englisch
           <dbl>    <dbl> <chr> <chr>         <dbl> <chr>      <dbl> <chr>
1           1034        3 mjölk Milch             1 Frau          51 B2
# i 1 more variable: RichtigeÜbersetzung <chr>
```

We can also select multiple rows:

```r
# Rows 5 and 7
all_data |>
  slice(c(5, 7))
```

```
# A tibble: 2 x 9
  Versuchsperson Position Wort     Übersetzung Richtig Geschlecht Alter Englisch
           <dbl>    <dbl> <chr>    <chr>         <dbl> <chr>      <dbl> <chr>
1           1034        5 fiende   finden            0 Frau          51 B2
2           2384        2 behärska <NA>              0 Frau          27 C1
# i 1 more variable: RichtigeÜbersetzung <chr>
```

```r
# Rows 5 to (and including) 7
all_data |>
  slice(5:7)
```

```
# A tibble: 3 x 9
  Versuchsperson Position Wort     Übersetzung Richtig Geschlecht Alter Englisch
           <dbl>    <dbl> <chr>    <chr>         <dbl> <chr>      <dbl> <chr>
1           1034        5 fiende   finden            0 Frau          51 B2
2           2384        1 fiende   <NA>              0 Frau          27 C1
3           2384        2 behärska <NA>              0 Frau          27 C1
# i 1 more variable: RichtigeÜbersetzung <chr>
```

The results of such actions can be stored as separate objects, for instance, like so:

```r
rows7_12 <- all_data |>
  slice(7:12)
rows7_12
```

```
# A tibble: 6 x 9
  Versuchsperson Position Wort     Übersetzung Richtig Geschlecht Alter Englisch
           <dbl>    <dbl> <chr>    <chr>         <dbl> <chr>      <dbl> <chr>
1           2384        2 behärska <NA>              0 Frau          27 C1
2           2384        3 försikt~ vorsichtig        1 Frau          27 C1
3           2384        4 mjölk    Milch             1 Frau          27 C1
4           2384        5 söka     Socke             0 Frau          27 C1
5           8667        1 mjölk    Milch             1 Frau          27 B2
6           8667        2 behärska <NA>              0 Frau          27 B2
# i 1 more variable: RichtigeÜbersetzung <chr>
```

We can export this new object as a CSV file like so:

```
write_csv(rows7_12, here("data", "rows7_12.csv"))
```

Selecting by values

Selecting rows by their number isn't too useful. But selecting rows satisfying some set of conditions is very useful. Here are a few examples:

```
# All data corresponding to the word 'fiende'
all_data |>
  filter(Wort == "fiende")
```

```
# A tibble: 4 x 9
  Versuchsperson Position Wort   Übersetzung Richtig Geschlecht Alter Englisch
           <dbl>    <dbl> <chr>  <chr>         <dbl> <chr>      <dbl> <chr>
1           1034        5 fiende finden            0 Frau          51 B2
2           2384        1 fiende <NA>              0 Frau          27 C1
3           8667        3 fiende finden            0 Frau          27 B2
4           5901        4 fiende feinde            1 Mann          15 B1
# i 1 more variable: RichtigeÜbersetzung <chr>
```

```
# Note: use '!=' for 'not equal to'.

# All data corresponding to participants older than 30
all_data |>
  filter(Alter > 30)
```

```
# A tibble: 5 x 9
  Versuchsperson Position Wort     Übersetzung Richtig Geschlecht Alter Englisch
           <dbl>    <dbl> <chr>    <chr>         <dbl> <chr>      <dbl> <chr>
1           1034        1 söka     Socken            0 Frau          51 B2
2           1034        2 försikt~ vorsichtig        1 Frau          51 B2
3           1034        3 mjölk    Milch             1 Frau          51 B2
4           1034        4 behärska <NA>              0 Frau          51 B2
5           1034        5 fiende   finden            0 Frau          51 B2
# i 1 more variable: RichtigeÜbersetzung <chr>
```

```
# Note: use '>=' for 'at least as old as',
#           '<=' for 'no older than',
#        and '<' for 'younger than'.
```

We can use `is.na` to check for missing values. Note the use of `!` to negate a condition.

```
all_data |>
  filter(is.na(Übersetzung))
```

```
# A tibble: 4 x 9
  Versuchsperson Position Wort     Übersetzung Richtig Geschlecht Alter Englisch
           <dbl>    <dbl> <chr>    <chr>         <dbl> <chr>      <dbl> <chr>
1           1034        4 behärska <NA>              0 Frau          51 B2
2           2384        1 fiende   <NA>              0 Frau          27 C1
3           2384        2 behärska <NA>              0 Frau          27 C1
4           8667        2 behärska <NA>              0 Frau          27 B2
# i 1 more variable: RichtigeÜbersetzung <chr>
```

```
all_data |>
  filter(!is.na(Übersetzung))
```

```
# A tibble: 16 x 9
   Versuchsperson Position Wort    Übersetzung Richtig Geschlecht Alter Englisch
            <dbl>    <dbl> <chr>   <chr>         <dbl> <chr>      <dbl> <chr>
 1           1034        1 söka    Socken            0 Frau          51 B2
 2           1034        2 försik~ vorsichtig        1 Frau          51 B2
 3           1034        3 mjölk   Milch             1 Frau          51 B2
 4           1034        5 fiende  finden            0 Frau          51 B2
 5           2384        3 försik~ vorsichtig        1 Frau          27 C1
 6           2384        4 mjölk   Milch             1 Frau          27 C1
```

```
 7          2384        5 söka    Socke             0 Frau            27 C1
 8          8667        1 mjölk   Milch             1 Frau            27 B2
 9          8667        3 fiende  finden            0 Frau            27 B2
10          8667        4 söka    suchen            1 Frau            27 B2
11          8667        5 försik~ vorsichtig        1 Frau            27 B2
12          5901        1 behärs~ beherrschen       1 Mann            15 B1
13          5901        2 mjölk   milch             1 Mann            15 B1
14          5901        3 försik~ vorsichtig        1 Mann            15 B1
15          5901        4 fiende  feinde            1 Mann            15 B1
16          5901        5 söka    socken            0 Mann            15 B1
# i 1 more variable: RichtigeÜbersetzung <chr>
```

We can string together multiple `filter` calls:

```r
# incorrect translations to first word
all_data |>
  filter(Position == 1) |>
  filter(Richtig == 0)
```

```
# A tibble: 2 x 9
  Versuchsperson Position Wort   Übersetzung Richtig Geschlecht Alter Englisch
           <dbl>    <dbl> <chr>  <chr>         <dbl> <chr>      <dbl> <chr>
1           1034        1 söka   Socken            0 Frau          51 B2
2           2384        1 fiende <NA>              0 Frau          27 C1
# i 1 more variable: RichtigeÜbersetzung <chr>
```

An alternative way of writing this is as follows:

```r
all_data |>
  filter(Position == 1 & Richtig == 0)
```

```
# A tibble: 2 x 9
  Versuchsperson Position Wort   Übersetzung Richtig Geschlecht Alter Englisch
           <dbl>    <dbl> <chr>  <chr>         <dbl> <chr>      <dbl> <chr>
1           1034        1 söka   Socken            0 Frau          51 B2
2           2384        1 fiende <NA>              0 Frau          27 C1
# i 1 more variable: RichtigeÜbersetzung <chr>
```

‘or’ conditions can be created using `|`:

```r
# translations to first word or incorrect translations
all_data |>
  filter(Position == 1 | Richtig == 0)
```

```
# A tibble: 11 x 9
   Versuchsperson Position Wort    Übersetzung Richtig Geschlecht Alter Englisch
            <dbl>    <dbl> <chr>   <chr>         <dbl> <chr>      <dbl> <chr>
 1           1034        1 söka    Socken            0 Frau          51 B2
 2           1034        4 behärs~ <NA>              0 Frau          51 B2
 3           1034        5 fiende  finden            0 Frau          51 B2
 4           2384        1 fiende  <NA>              0 Frau          27 C1
 5           2384        2 behärs~ <NA>              0 Frau          27 C1
 6           2384        5 söka    Socke             0 Frau          27 C1
 7           8667        1 mjölk   Milch             1 Frau          27 B2
 8           8667        2 behärs~ <NA>              0 Frau          27 B2
 9           8667        3 fiende  finden            0 Frau          27 B2
10           5901        1 behärs~ beherrschen       1 Mann          15 B1
11           5901        5 söka    socken            0 Mann          15 B1
# i 1 more variable: RichtigeÜbersetzung <chr>
```

Note that in logic, 'or' is always inclusive. Exclusive 'or' ('xor') can be obtained as follows:

```r
# translations to first word or incorrect translations, but not both
all_data |>
  filter(Position == 1 | Richtig == 0) |>
  filter(!(Position == 1 & Richtig == 0))
```

```
# A tibble: 9 x 9
  Versuchsperson Position Wort     Übersetzung Richtig Geschlecht Alter Englisch
           <dbl>    <dbl> <chr>    <chr>         <dbl> <chr>      <dbl> <chr>
1           1034        4 behärska <NA>              0 Frau          51 B2
2           1034        5 fiende   finden            0 Frau          51 B2
3           2384        2 behärska <NA>              0 Frau          27 C1
4           2384        5 söka     Socke             0 Frau          27 C1
5           8667        1 mjölk    Milch             1 Frau          27 B2
6           8667        2 behärska <NA>              0 Frau          27 B2
7           8667        3 fiende   finden            0 Frau          27 B2
8           5901        1 behärska beherrschen       1 Mann          15 B1
9           5901        5 söka     socken            0 Mann          15 B1
# i 1 more variable: RichtigeÜbersetzung <chr>
```

Alternatively,

```r
all_data |>
  filter(xor(Position == 1, Richtig == 0))
```

```
# A tibble: 9 x 9
  Versuchsperson Position Wort     Übersetzung Richtig Geschlecht Alter Englisch
           <dbl>    <dbl> <chr>    <chr>         <dbl> <chr>      <dbl> <chr>
1           1034        4 behärska <NA>              0 Frau          51 B2
2           1034        5 fiende   finden            0 Frau          51 B2
3           2384        2 behärska <NA>              0 Frau          27 C1
4           2384        5 söka     Socke             0 Frau          27 C1
5           8667        1 mjölk    Milch             1 Frau          27 B2
6           8667        2 behärska <NA>              0 Frau          27 B2
7           8667        3 fiende   finden            0 Frau          27 B2
8           5901        1 behärska beherrschen       1 Mann          15 B1
9           5901        5 söka     socken            0 Mann          15 B1
# i 1 more variable: RichtigeÜbersetzung <chr>
```

Exercise

1. Run the following commands:

```r
d1 <- all_data |>
  filter(Übersetzung == "vorsichtig")
d2 <- all_data |>
  filter(Übersetzung != "vorsichtig")
```

2. Explain what both commands achieve.
3. How many rows are there in `d1`? How many in `d2`? How many in `all_data`? Explain.
4. Create a tibble `d3` that contains only those rows in `all_data` where the participants did not translate the word as *vorsichtig*.

Selecting columns

Sometimes, a dataset is too cumbersome to handle because it contains a lot of irrelevant columns. Using `select`, we can select those columns that are of interest. For instance,

```r
all_data |>
  select(Wort, RichtigeÜbersetzung, Übersetzung) |>
  slice_head(n = 5)
```

```
# A tibble: 5 x 3
  Wort      RichtigeÜbersetzung Übersetzung
  <chr>     <chr>               <chr>
1 söka      suchen              Socken
2 försiktig vorsichtig          vorsichtig
3 mjölk     milch               Milch
4 behärska  beherrschen         <NA>
5 fiende    Feind               finden
```

There are a couple of auxiliary functions that make it easier to select columns. These are especially useful when working with large datasets. Examples are `contains()` and `starts_with()`:

```r
all_data |>
  select(contains("Übersetzung"))
```

```
# A tibble: 20 x 2
   Übersetzung RichtigeÜbersetzung
   <chr>       <chr>
 1 Socken      suchen
 2 vorsichtig  vorsichtig
 3 Milch       milch
 4 <NA>        beherrschen
 5 finden      Feind
 6 <NA>        Feind
 7 <NA>        beherrschen
 8 vorsichtig  vorsichtig
 9 Milch       milch
10 Socke       suchen
11 Milch       milch
12 <NA>        beherrschen
13 finden      Feind
14 suchen      suchen
15 vorsichtig  vorsichtig
16 beherrschen beherrschen
17 milch       milch
```

```
18 vorsichtig  vorsichtig
19 feinde      Feind
20 socken      suchen
```

```
all_data |>
  select(starts_with("Richt"))
```

```
# A tibble: 20 x 2
   Richtig RichtigeÜbersetzung
     <dbl> <chr>
 1       0 suchen
 2       1 vorsichtig
 3       1 milch
 4       0 beherrschen
 5       0 Feind
 6       0 Feind
 7       0 beherrschen
 8       1 vorsichtig
 9       1 milch
10       0 suchen
11       1 milch
12       0 beherrschen
13       0 Feind
14       1 suchen
15       1 vorsichtig
16       1 beherrschen
17       1 milch
18       1 vorsichtig
19       1 Feind
20       0 suchen
```

See the tidyselect documentation for further functions.

Further examples

We can string together different types of commands:

```
# All translations for 'fiende'
all_data |>
  filter(Wort == "fiende") |>
```

```
  select(Übersetzung)
```

```
# A tibble: 4 x 1
  Übersetzung
  <chr>
1 finden
2 <NA>
3 finden
4 feinde
```

```
# All *distinct* translations for 'behärska':
all_data |>
  filter(Wort == "behärska") |>
  select(Übersetzung) |>
  distinct()
```

```
# A tibble: 2 x 1
  Übersetzung
  <chr>
1 <NA>
2 beherrschen
```

Without the pipe (`|>`), these commands become difficult to read:

```
distinct(select(filter(all_data, Wort == "behärska"), Übersetzung))
```

```
# A tibble: 2 x 1
  Übersetzung
  <chr>
1 <NA>
2 beherrschen
```

Pivoting

In the course of an analysis, it is often necessary to convert a long-ish dataset to a wider one, and vice versa. This process is known as *pivoting*. To illustrate pivoting, we'll make use of a more realistic – and more complicated – dataset derived from a longitudinal project on the development of reading and writing skills in Portuguese–French and Portuguese–German bilingual children (Desgrippes et al. 2017, Pestana et al. 2017).

We read in the dataset `helascot_skills.csv` as `skills`:

```
skills <- read_csv(here("data", "helascot_skills.csv"))
```

```
Rows: 1904 Columns: 6
-- Column specification ---------------------------------------------------------
Delimiter: ","
chr (2): Subject, LanguageTested
dbl (4): Time, Reading, Argumentation, Narration

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
skills
```

```
# A tibble: 1,904 x 6
   Subject   Time LanguageTested Reading Argumentation Narration
   <chr>    <dbl> <chr>            <dbl>         <dbl>     <dbl>
 1 A_PLF_1      1 French           0.211             7        NA
 2 A_PLF_1      1 Portuguese       0.579             9         6
 3 A_PLF_1      2 French           0.684            14        10
 4 A_PLF_1      2 Portuguese       0.737            13         9
 5 A_PLF_1      3 French           0.947            14         8
 6 A_PLF_1      3 Portuguese       0.842            13        NA
 7 A_PLF_10     1 French           0.579             5        10
 8 A_PLF_10     1 Portuguese       0.316             6         7
 9 A_PLF_10     2 French           0.474            10         8
10 A_PLF_10     2 Portuguese       0.579             7        NA
# i 1,894 more rows
```

For each participant (`Subject`) at each `Time` (T1, T2, T3) and for each `LanguageTested` (Portuguese, French, German), we have up to three scores, `Reading`, `Argumentation` and `Narration`, arranged next to each other. But let's say we wanted to compute, for each participant, their progress on each task in each language from T1 to T2 and from T2 to T3. The way the data are laid out at present, this would at best be pretty difficult to do. But it would be easy if only the data were arranged differently, namely with all three measurements per participant and task next to each other. We can convert this dataset to the desired format in two steps.

First, we make the dataset longer by stacking the different scores under each other rather than next to each other. To this end, we use the function `pivot_longer()` and specify that we want to stack the values in the `Reading`, `Argumentation`, and `Narration` columns under each other, that we want to call the resulting column `Score`, and that we want to put the column names in a new column called `Skill`:

```
skills_longer <- skills |>
  pivot_longer(cols = c("Reading", "Argumentation", "Narration"),
               names_to = "Skill", values_to = "Score")
skills_longer
```

```
# A tibble: 5,712 x 5
   Subject  Time LanguageTested Skill          Score
   <chr>   <dbl> <chr>          <chr>          <dbl>
 1 A_PLF_1     1 French         Reading        0.211
 2 A_PLF_1     1 French         Argumentation  7
 3 A_PLF_1     1 French         Narration     NA
 4 A_PLF_1     1 Portuguese     Reading        0.579
 5 A_PLF_1     1 Portuguese     Argumentation  9
 6 A_PLF_1     1 Portuguese     Narration      6
 7 A_PLF_1     2 French         Reading        0.684
 8 A_PLF_1     2 French         Argumentation 14
 9 A_PLF_1     2 French         Narration     10
10 A_PLF_1     2 Portuguese     Reading        0.737
# i 5,702 more rows
```

Then, we make this tibble wider by putting the three measurements per skill and language next to each other using `pivot_wider()`. We also prefix the `Time` values with a `T`.

```
skills_wider_time <- skills_longer |>
  pivot_wider(names_from = Time, values_from = Score,
              names_prefix = "T")
skills_wider_time
```

```
# A tibble: 2,100 x 6
   Subject  LanguageTested Skill              T1     T2     T3
   <chr>    <chr>          <chr>           <dbl>  <dbl>  <dbl>
 1 A_PLF_1  French         Reading         0.211  0.684  0.947
 2 A_PLF_1  French         Argumentation   7     14     14
 3 A_PLF_1  French         Narration      NA     10      8
 4 A_PLF_1  Portuguese     Reading         0.579  0.737  0.842
 5 A_PLF_1  Portuguese     Argumentation   9     13     13
 6 A_PLF_1  Portuguese     Narration       6      9     NA
```

```
 7 A_PLF_10 French         Reading        0.579  0.474  0.316
 8 A_PLF_10 French         Argumentation  5     10     13
 9 A_PLF_10 French         Narration     10      8      8
10 A_PLF_10 Portuguese     Reading        0.316  0.579  0.368
# i 2,090 more rows
```

Using `mutate()`, we can now easily compute the differences between `T1` and `T2` and between `T2` and `T3`:

```
skills_wider_time |>
  mutate(ProgressT1_T2 = T2 - T1,
         ProgressT2_T3 = T3 - T2) |>
  select(Subject, LanguageTested, Skill, ProgressT1_T2, ProgressT2_T3)
```

```
# A tibble: 2,100 x 5
   Subject  LanguageTested Skill         ProgressT1_T2 ProgressT2_T3
   <chr>    <chr>          <chr>                 <dbl>         <dbl>
 1 A_PLF_1  French         Reading               0.474         0.263
 2 A_PLF_1  French         Argumentation         7             0
 3 A_PLF_1  French         Narration            NA            -2
 4 A_PLF_1  Portuguese     Reading               0.158         0.105
 5 A_PLF_1  Portuguese     Argumentation         4             0
 6 A_PLF_1  Portuguese     Narration             3            NA
 7 A_PLF_10 French         Reading              -0.105        -0.158
 8 A_PLF_10 French         Argumentation         5             3
 9 A_PLF_10 French         Narration            -2             0
10 A_PLF_10 Portuguese     Reading               0.263        -0.211
# i 2,090 more rows
```

Now imagine that we wanted to compute, for each participant in each skill at each data collection, the difference between the Portuguese score and the German/French score. The first step is the same, resulting in `skills_longer`. The second step is now similar, but we put the different languages next to each other:

```
skills_wider_language <- skills_longer |>
  pivot_wider(names_from = LanguageTested, values_from = Score)
skills_wider_language
```

```
# A tibble: 3,999 x 6
   Subject   Time Skill         French Portuguese German
```

```
   <chr>    <dbl> <chr>          <dbl>      <dbl>  <dbl>
 1 A_PLF_1      1 Reading        0.211      0.579     NA
 2 A_PLF_1      1 Argumentation  7          9         NA
 3 A_PLF_1      1 Narration     NA          6         NA
 4 A_PLF_1      2 Reading        0.684      0.737     NA
 5 A_PLF_1      2 Argumentation 14         13         NA
 6 A_PLF_1      2 Narration     10          9         NA
 7 A_PLF_1      3 Reading        0.947      0.842     NA
 8 A_PLF_1      3 Argumentation 14         13         NA
 9 A_PLF_1      3 Narration      8         NA         NA
10 A_PLF_10     1 Reading        0.579      0.316     NA
# i 3,989 more rows
```

Incidentally, not all values for `German` are `NA`. It's just that the first couple of children were tested in French and Portuguese, not in German. We can check this like so:

```r
skills_wider_language |>
  slice_sample(n = 10)
```

```
# A tibble: 10 x 6
   Subject    Time Skill         French Portuguese German
   <chr>     <dbl> <chr>          <dbl>      <dbl>  <dbl>
 1 R_CF_13       3 Reading        0.632     NA     NA
 2 T_CF_11       3 Reading        0.368     NA     NA
 3 AL_CP_19      2 Reading       NA          0.632 NA
 4 Y_PNF_20      3 Narration      7          8     NA
 5 U_CD_9        3 Reading       NA         NA      0.737
 6 E_PLD_15      2 Argumentation NA         12     NA
 7 Q_CF_9        1 Argumentation 16         NA     NA
 8 AD_PLF_24     2 Narration      5          7     NA
 9 Z_PLF_7       2 Narration     12          8     NA
10 H_PLD_7       2 Narration     NA          7     NA
```

If we needed to, we could make this dataset wider still:

```r
skills_wider_time_language <- skills_longer |>
  pivot_wider(names_from = c(LanguageTested, Time), # combination of Language and Time
              values_from = Score)
skills_wider_time_language
```

```
# A tibble: 1,410 x 11
   Subject  Skill         French_1 Portuguese_1 French_2 Portuguese_2 French_3
   <chr>    <chr>            <dbl>        <dbl>    <dbl>        <dbl>    <dbl>
 1 A_PLF_1  Reading          0.211        0.579    0.684        0.737    0.947
 2 A_PLF_1  Argumentation    7            9       14           13       14
 3 A_PLF_1  Narration       NA            6       10            9        8
 4 A_PLF_10 Reading          0.579        0.316    0.474        0.579    0.316
 5 A_PLF_10 Argumentation    5            6       10            7       13
 6 A_PLF_10 Narration       10            7        8           NA        8
 7 A_PLF_12 Reading          0.895       NA        1            0.947    0.947
 8 A_PLF_12 Argumentation   10           NA       17           18       21
 9 A_PLF_12 Narration       11           NA       14           12       12
10 A_PLF_13 Reading          0.474        0.316    0.421        0.526    0.579
# i 1,400 more rows
# i 4 more variables: Portuguese_3 <dbl>, German_1 <dbl>, German_2 <dbl>,
#   German_3 <dbl>
```

We could reconvert this tibble to a long one using the code snippet below. The code becomes a bit more complex: The notation `French_1:German_3` selects all columns between `French_1` and `German_3` (including), whereas a so-called *regular expression* (regex) is used to parse these column names into the `Language` bit and into the `Time` bit. For the present example, we don't need this code snippet since we already have `skills_longer`. But I wanted to illustrate that such conversions are *possible*. If you ever need to convert a similar dataset to a longer format, you now know that you can look up the details on the help page of `pivot_longer()` (`?pivot_longer`) and take it from there:

```
skills_wider_time_language |>
  pivot_longer(cols = French_1:German_3,
               names_to = c("Language", "Time"),
               names_pattern = "(.*)_(.*)",
               values_to = "Score")
```

```
# A tibble: 12,690 x 5
   Subject Skill         Language   Time   Score
   <chr>   <chr>         <chr>      <chr>  <dbl>
 1 A_PLF_1 Reading       French     1      0.211
 2 A_PLF_1 Reading       Portuguese 1      0.579
 3 A_PLF_1 Reading       French     2      0.684
 4 A_PLF_1 Reading       Portuguese 2      0.737
 5 A_PLF_1 Reading       French     3      0.947
 6 A_PLF_1 Reading       Portuguese 3      0.842
 7 A_PLF_1 Reading       German     1     NA
```

```
 8 A_PLF_1 Reading       German     2      NA
 9 A_PLF_1 Reading       German     3      NA
10 A_PLF_1 Argumentation French     1       7
# i 12,680 more rows
```

Alternatively, we could have used `starts_with(c("French", "Portuguese", "German"))` to select the relevant columns.

Summaries

Using the `summarise()` function, we can easily summarise large tibbles. For instance, we can compute the average (mean) narration and argumentation scores in the `skills` tibble like so:

```
skills |>
  summarise(mean_narr = mean(Narration, na.rm = TRUE),
            mean_arg  = mean(Argumentation, na.rm = TRUE))
```

```
# A tibble: 1 x 2
  mean_narr mean_arg
      <dbl>    <dbl>
1      8.51     13.0
```

We set the `na.rm` parameter in the `mean()` call to `TRUE` since there are several missing observations in both the `Narration` and `Argumentation` variable. If we didn't set `na.rm` to `TRUE`, the result of both computations would be `NA`. By setting `na.rm` to `TRUE`, missing observations are ignored.

`summarise()` is often used in conjuction with `group_by()`, which splits up a tibble into subgroups. This way, we can straightforwardly compute summaries for different subgroups. For instance, if we wanted to compute the mean narration and argumentation scores for each time of data collection and each language tested, we could use the following code snippet:

```
skills |>
  group_by(Time, LanguageTested) |>
  summarise(mean_narr = mean(Narration, na.rm = TRUE),
            mean_arg  = mean(Argumentation, na.rm = TRUE),
            .groups = "drop")
```

```
# A tibble: 9 x 4
   Time LanguageTested mean_narr mean_arg
  <dbl> <chr>              <dbl>    <dbl>
1     1 French              7.79    11.2
2     1 German              6.33     9.46
3     1 Portuguese          8.50    11.4
4     2 French              8.37    13.2
5     2 German              7.06    12.2
6     2 Portuguese          9.16    13.3
7     3 French             10.1     16.3
8     3 German              7.68    13.2
9     3 Portuguese         10.2     16
```

By setting `.groups = "drop"`, you make sure that the grouping applied to `skills` doesn't apply to the summary tibble any more. (It's not so important.)

We can treat these summary tibbles like ordinary tibbles and apply all of the other commands to them:

```
skills |>
  group_by(Time, LanguageTested) |>
  summarise(mean_narr = mean(Narration, na.rm = TRUE),
            .groups = "drop") |>
  pivot_wider(names_from = "Time", names_prefix = "T", values_from = "mean_narr")
```

```
# A tibble: 3 x 4
  LanguageTested    T1    T2    T3
  <chr>          <dbl> <dbl> <dbl>
1 French          7.79  8.37 10.1
2 German          6.33  7.06  7.68
3 Portuguese      8.50  9.16 10.2
```

In addition to `mean()`, here are some further functions that are often used when computing summaries; see the functions' help pages for details:

- `median()`,
- `quantile()`,
- `min()` and `max()`,
- `sd()` and `var()` for the sample standard deviation and sample variance, respectively,
- `mad()` for the (adjusted) median absolute deviation,
- `n()` for obtaining the number of observations,
- `sum()`.

The `mean()` function can also be used to compute proportions. Consider the following example. The `is.na()` function checks if a value is `NA` (in which case it returns `TRUE`) or not (`FALSE`). If we compute the `mean()` of a bunch of `TRUE/FALSE` values, we obtain the proportion of values that are `TRUE`. Similarly, the `sum()` of a bunch of `TRUE/FALSE` values is the number of `TRUE` values. Hence, we can quickly obtain the proportion, and number, of the missing `Narration` scores for each combination of `Time` and `LanguageTested`:

```
skills |>
  group_by(Time, LanguageTested) |>
  summarise(
    prop_narr_NA = mean(is.na(Narration)),
    nr_narr_NA = sum(is.na(Narration)),
    n = n(),
    .groups = "drop"
  )
```

```
# A tibble: 9 x 5
   Time LanguageTested prop_narr_NA nr_narr_NA     n
  <dbl> <chr>                 <dbl>      <int> <int>
1     1 French               0.297          54   182
2     1 German               0.0815         15   184
3     1 Portuguese           0.141          40   284
4     2 French               0.120          22   183
5     2 German               0.0862         15   174
6     2 Portuguese           0.129          36   280
7     3 French               0.0632         11   174
8     3 German               0.0581         10   172
9     3 Portuguese           0.0923         25   271
```

Writing your own functions

You can write your own functions. For instance, an alternative to the mean and the median is the Hodges–Lehmann estimator. We can define a function that computes this estimator like so:

```r
hodges_lehmann <- function(x, na.rm = TRUE) {
  if (na.rm) {
    x <- x[!is.na(x)]
  }
  pairwise_means <- outer(x, x, FUN = "+") / 2
  median(pairwise_means[upper.tri(pairwise_means, diag = TRUE)])
}
```

We can then use this function in `summarise()` like so,

```r
skills |>
  group_by(Time, LanguageTested) |>
  summarise(
    hl_narr = hodges_lehmann(Narration),
    .groups = "drop"
  ) |>
  pivot_wider(names_from = "Time", names_prefix = "T", values_from = "hl_narr")
```

```
# A tibble: 3 x 4
  LanguageTested    T1    T2    T3
  <chr>          <dbl> <dbl> <dbl>
1 French           7.5     8  10
2 German           6.5     7   7.5
3 Portuguese       8.5     9  10
```

String manipulation

It often happens that a single cell in a dataset contains different pieces of information. So, too, it is the case in our current example. The first participant in the dataset is referred to as `A_PLF_1`:

- The `A` in this ID refers to their class.
- The `PLF` tells us that this participant resided in French-speaking Switzerland (`F`), had a Portuguese background (`P`) and took Portuguese heritage and language courses (`L`). Other abbreviations in the dataset are `CD`, `CF`, and `CP` for comparison groups in German-speaking Switzerland, French-speaking Switzerland, and Portugal, respectively, `PLD` for participants residing in German-speaking Switzerland with a Portuguese background that attended a Portuguese course, as well as `PND` and `PNF` for participants in German- and French-speaking Switzerland, respectively, with a Portuguese background that did not take Portuguese classes.

- The `1` uniquely identifies this participant within its class.

It could make sense to split up the information contained in this one cell into multiple cells. Thankfully, the strings in `Subject` are structured logically and consistently: the different pieces of information are separated using underscores (`"_"`). We can hence split these strings at the underscores and retrieve the first and second pieces like so:

```
skills_wider_language <- skills_wider_language |>
  mutate(
    Class = str_split_i(Subject, "_", 1),
    Group = str_split_i(Subject, "_", 2)
  )
# check:
skills_wider_language |>
  select(Subject, Class, Group) |>
  sample_n(10)
```

```
# A tibble: 10 x 3
   Subject  Class Group
   <chr>    <chr> <chr>
 1 Q_CF_5   Q     CF
 2 O_PLD_16 O     PLD
 3 AL_CP_9  AL    CP
 4 R_CF_17  R     CF
 5 L_PLD_9  L     PLD
 6 W_CF_20  W     CF
 7 E_PLD_4  E     PLD
 8 AL_CP_21 AL    CP
 9 AI_CP_7  AI    CP
10 R_CF_9   R     CF
```

The examples/exercises will showcase some further applications of string manipulation, but I refer to the stringr documentation for further guidance.

We can now further break down the information contained in the new `Group` column, for instance as follows:

```
skills_wider_language <- skills_wider_language |>
  mutate(language_group = case_when(
    Group == "CP" ~ "Portuguese control",
    Group == "CF" ~ "French control",
    Group == "CD" ~ "German control",
```

```r
    Group %in% c("PLF", "PNF") ~ "French-Portuguese",
    Group %in% c("PLD", "PND") ~ "German-Portuguese",
    .default =  "other"
  )) |>
  mutate(heritage_course = case_when(
    Group %in% c("PLF", "PLD") ~ 1,
    .default =  0
  )) |>
  mutate(has_German = case_when(
    Group %in% c("CD", "PLD", "PND") ~ 1,
    .default =  0
  )) |>
  mutate(has_French = case_when(
    Group %in% c("CF", "PLF", "PNF") ~ 1,
    .default =  0
  )) |>
  mutate(has_Portuguese = case_when(
    Group %in% c("CF", "CD") ~ 0,
    .default =  1
  ))

# check:
skills_wider_language |>
  select(Subject, language_group, heritage_course, has_German, has_French, has_Portuguese)
  sample_n(10)
```

```
# A tibble: 10 x 6
   Subject  language_group  heritage_course has_German has_French has_Portuguese
   <chr>    <chr>                     <dbl>      <dbl>      <dbl>          <dbl>
 1 AG_PLD_2 German-Portugu~               1          1          0              1
 2 X_PND_1  German-Portugu~               0          1          0              1
 3 AK_CP_19 Portuguese con~               0          0          0              1
 4 AD_PLF_3 French-Portugu~               1          0          1              1
 5 AI_CP_19 Portuguese con~               0          0          0              1
 6 AC_PLD_4 German-Portugu~               1          1          0              1
 7 L_PLD_13 German-Portugu~               1          1          0              1
 8 L_PLD_14 German-Portugu~               1          1          0              1
 9 AL_CP_24 Portuguese con~               0          0          0              1
10 M_PLD_8  German-Portugu~               1          1          0              1
```

A full-fledged example

We had the children in the French/German/Portuguese project write short narrative and argumentative texts in each of their languages at three points in time. The quality of these texts was scored using a grid (Desgrippes et al. 2017); it is these scores that are listed in the `skills` tibble we worked with above. In addition, 3,060 of these texts were rated for their lexical richness by between two and eighteen naïve (i.e., non-instructed) raters each using a 1-to-9 scale. The individual ratings are available in the file `helascot_ratings.csv`. Furthermore, we computed a bunch of lexical metrics for each text, such as the number of tokens, the mean corpus frequency of the words occurring in the text, etc. These metric are avilable in the file `helascot_metrics.csv`; see Vanhove et al. (2019) and Vanhove (2019) for details.

We'll use these datasets to answer three questions:

- What's the relation between the average lexical richness ratings per text and the text's Guiraud index? (The Guiraud index is the ratio of the number of types in a text and the square root of the number of tokens in that text.)
- What's the relation between the average lexical richness ratings per text and the mean corpus frequency of the words occuring in the texts?
- What's the relation between the grid-based ratings and the lexical richness ratings?

In doing so, we'll need to make use of some of the tools introduced earlier.

Reading in the data

Let's start from a clean slate and read in the three datasets:

```
skills <- read_csv(here("data", "helascot_skills.csv"))
```

```
Rows: 1904 Columns: 6
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (2): Subject, LanguageTested
dbl (4): Time, Reading, Argumentation, Narration

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
metrics <- read_csv(here("data", "helascot_metrics.csv"))
```

```
Rows: 3060 Columns: 137
-- Column specification --------------------------------------------------------
Delimiter: ","
chr   (8): Text, Subject, Text_Language, Text_Type, LemmawordsNotInSUBTLEX, ...
dbl (129): Time, TTR, Guiraud, nTokens, nTypes, nLemmas, meanWordLength, MST...

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
ratings <- read_csv(here("data", "helascot_ratings.csv"))
```

```
Rows: 29179 Columns: 20
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (15): Batch, Rater, Text, Subject, Text_Language, Text_Type, Rater_Sex, ...
dbl  (4): Trial, Rating, Time, Rater_Age
lgl  (1): Rater_NativeLanguageOther

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

Inspect the structure of these three datasets. (**How?**) Note that

- `skills` contains one row per combination of `Subject`, `Time` and `LanguageTested`;
- `metrics` contains one row per text, i.e., one row per combination of `Subject`, `Text_Language`, `Text_Type` and `Time`;
- `ratings` contains one row per rating, i.e., one row per combination of `Rater` and `Text`.

> **i Note**
>
> These datasets are already pretty clean and a lot of work (partly manual, partly using R, partly using other tools) went into creating them. See the technical report as well as the R code available from osf.io.

There are many ways to skin a cat. But it seems to me that the following course of action is reasonable:

1. Using `ratings`, compute the average `Rating` per text.
2. Add these average ratings to `metrics` and draw some plots. (More on plotting in the second part!)
3. Make `skills` longer and add the average ratings to it. Then draw some more plots.

Average rating per text

```
rating_per_text <- ratings |>
  group_by(Text, Subject, Text_Language, Text_Type, Time) |>
  summarise(mean_rating = mean(Rating),
            n_ratings = n(),
            .groups = "drop")
```

Exercise

Some of the raters consider themselves native speakers of several languages (`bi-French` etc.), others consider themselves monolingual native speakers (`mono-French` etc.):

```
table(ratings$Rater_NativeLanguage)
```

```
      bi-French       bi-German   bi-Portuguese     mono-French     mono-German
           1049            2241             728            6235           14149
mono-Portuguese
           4777
```

What could you do if you wanted to base the average rating per text only on the ratings provided by monolingual raters?

Add to `metrics`

The tibbles `metrics` and `rating_per_text` share a variable (`Text`), so the average ratings can easily be added to `metrics`:

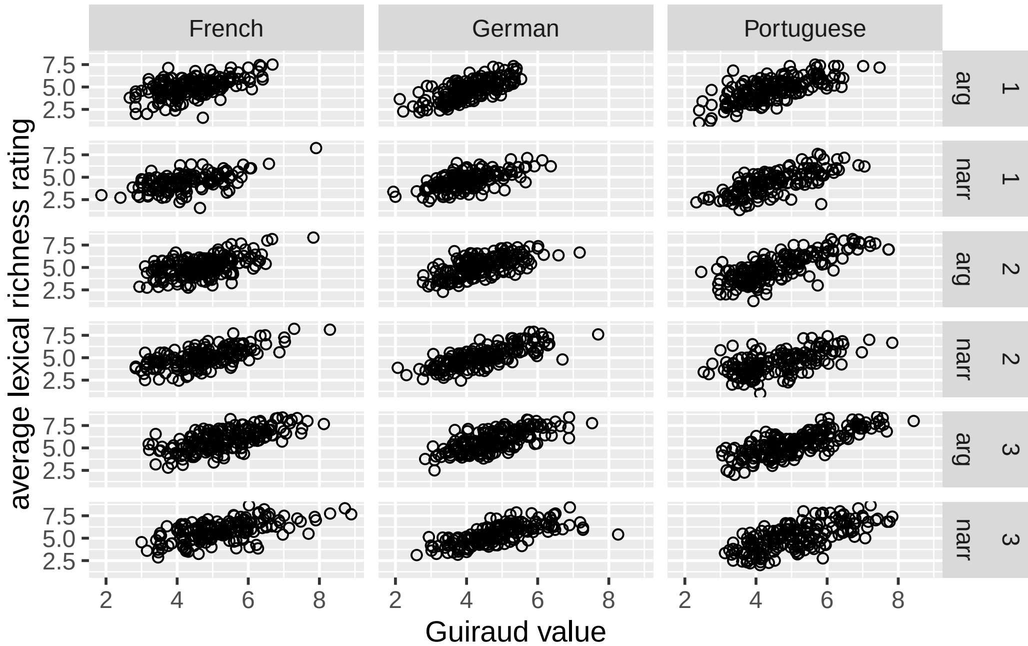
```
metrics_ratings <- metrics |>
  left_join(rating_per_text)
```

```
Joining with `by = join_by(Text, Subject, Text_Language, Text_Type, Time)`
```

We'll learn in the second part how to draw meaningful data plots, but here's one way of visualising the relationship between `Guiraud` and `mean_rating`:

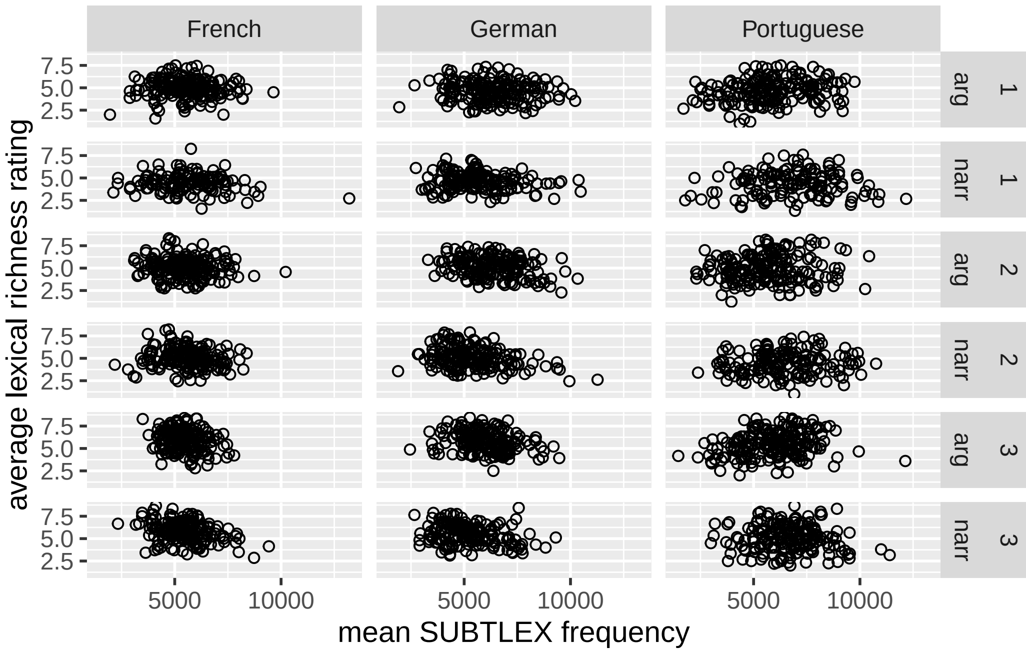
```
metrics_ratings |>
  ggplot(aes(x = Guiraud, y = mean_rating)) +
  geom_point(shape = 1) +
```

```
  facet_grid(rows = vars(Time, Text_Type),
             cols = vars(Text_Language)) +
  xlab("Guiraud value") +
  ylab("average lexical richness rating")
```



Similarly, for `meanSUBTLEX` (average corpus frequency):

```
metrics_ratings |>
  ggplot(aes(x = meanSUBTLEX, y = mean_rating)) +
  geom_point(shape = 1) +
  facet_grid(rows = vars(Time, Text_Type),
             cols = vars(Text_Language)) +
  xlab("mean SUBTLEX frequency") +
  ylab("average lexical richness rating")
```




```
correlations <- metrics_ratings |>
  group_by(Text_Language, Time, Text_Type) |>
  summarise(
    cor_guiraud = cor(mean_rating, Guiraud),
    cor_frequency = cor(mean_rating, meanSUBTLEX)
  )
```

```
`summarise()` has grouped output by 'Text_Language', 'Time'. You can override
using the `.groups` argument.
```

```
correlations
```

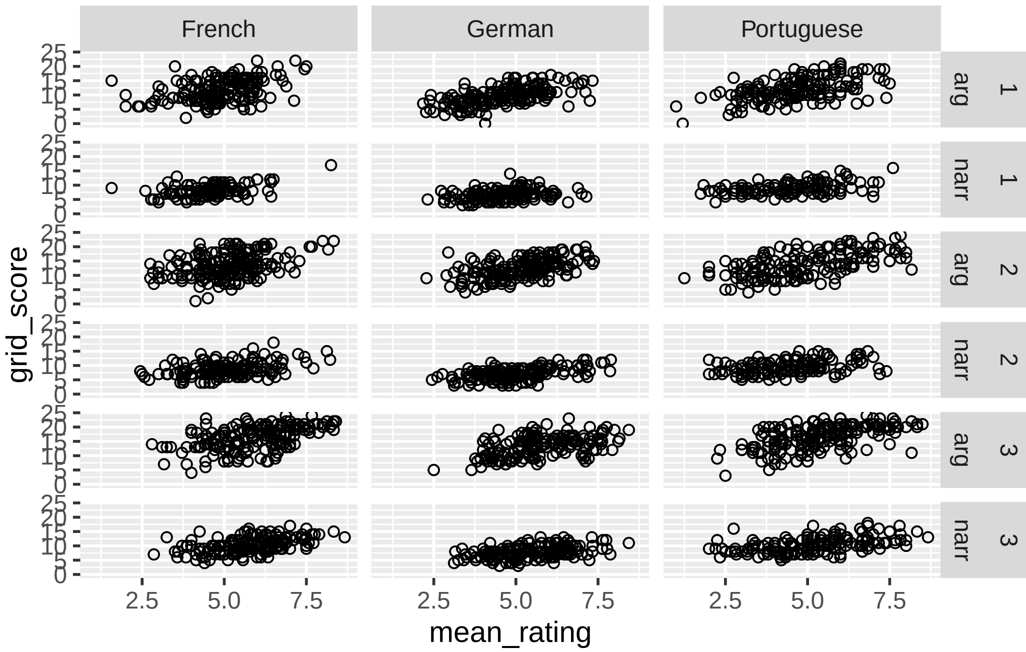
```
# A tibble: 18 x 5
   Text_Language  Time Text_Type cor_guiraud cor_frequency
   <chr>         <dbl> <chr>           <dbl>         <dbl>
 1 French            1 arg             0.526       -0.0353
 2 French            1 narr            0.565       -0.150
 3 French            2 arg             0.525       -0.0847
 4 French            2 narr            0.657       -0.0964
 5 French            3 arg             0.654       -0.205
```

```
 6 French           3 narr            0.618       -0.299
 7 German           1 arg             0.710       -0.0747
 8 German           1 narr            0.616       -0.162
 9 German           2 arg             0.643       -0.288
10 German           2 narr            0.758       -0.314
11 German           3 arg             0.694       -0.241
12 German           3 narr            0.704       -0.257
13 Portuguese       1 arg             0.703        0.196
14 Portuguese       1 narr            0.716        0.0248
15 Portuguese       2 arg             0.764        0.0662
16 Portuguese       2 narr            0.605        0.0729
17 Portuguese       3 arg             0.777        0.222
18 Portuguese       3 narr            0.692       -0.0693
```

Add to `skills`

```r
rating_gridscore <- skills |>
  pivot_longer(Reading:Narration, names_to = "skill",
               values_to = "grid_score") |>
  filter(skill != "Reading") |>
  mutate(Text_Type = case_when(
    skill == "Argumentation" ~ "arg",
    skill == "Narration" ~ "narr"
  )) |>
  full_join(rating_per_text,
            by = join_by(Text_Type, Subject, Time, LanguageTested == Text_Language))
```

```r
rating_gridscore |>
  filter(!is.na(grid_score)) |>
  filter(!is.na(mean_rating)) |>
  ggplot(aes(x = mean_rating, y = grid_score)) +
  geom_point(shape = 1) +
  facet_grid(rows = vars(Time, Text_Type),
             cols = vars(LanguageTested))
```




```
rating_gridscore |>
  filter(!is.na(grid_score)) |>
  filter(!is.na(mean_rating)) |>
  group_by(LanguageTested, Time, Text_Type) |>
  summarise(
    cor_score = cor(mean_rating, grid_score),
    .groups = "drop"
  )
```

```
# A tibble: 18 x 4
   LanguageTested  Time Text_Type cor_score
   <chr>          <dbl> <chr>         <dbl>
 1 French             1 arg           0.391
 2 French             1 narr          0.445
 3 French             2 arg           0.395
 4 French             2 narr          0.389
 5 French             3 arg           0.490
 6 French             3 narr          0.487
 7 German             1 arg           0.585
 8 German             1 narr          0.282
 9 German             2 arg           0.522
10 German             2 narr          0.512
```

```
11 German                3 arg             0.499
12 German                3 narr            0.428
13 Portuguese            1 arg             0.528
14 Portuguese            1 narr            0.417
15 Portuguese            2 arg             0.572
16 Portuguese            2 narr            0.372
17 Portuguese            3 arg             0.557
18 Portuguese            3 narr            0.506
```

Suggestions for reading

The Bible for working with tibbles in R is Wickham et al.'s *R for Data Science*, which is freely available from r4ds.hadley.nz.