Week 2: Tabular Data

LSE MY472: Data for Data Scientists https://lse-my472.github.io/

Autumn Term 2024

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Plan for today

- → "Tidy data" and reshaping data in R
- → Some good practises for code in (research) projects
- → Coding

"Tidy data" and reshaping data in R

What is data?

- → We can distinguish data . . .
 - → Representations, symbols, variables
 - → E.g. "All", "the", "world's", "a", "stage"
- → ... from information
 - The meaning and context we gain from organizing and assembling data
 - → E.g. "All the world's a stage"
- → Data are a convenient way of *storing* and *transmitting* information
 - → See Caleb Sharf's "The Ascent of Information" (2021)

Shapes of data

- → One very common form of data is tabular
- → Examples of other forms: Raw texts, key-value and array structures such as JSON files
- → This week: How to organise and process tabular data (in R)
- → Helpful to think about an ideal format of tabular data first

Comparing data structures

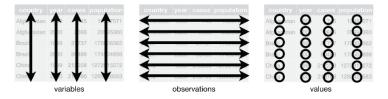
```
tweet tags blist blist_descriptions 

1 I think MY472 is the best course ever LSF, MY472 asds_tweets, publicity my thoughts, to share
```

"Tidy" data (Hadley Wickham)

Three rules:

- 1. Each variable must have its own column
- 2. Each observation must have its own row
- 3. Each value must have its own cell



Section based on https://r4ds.had.co.nz/tidy-data.html

What can go wrong?

Datasets where columns represent values of a variable:

How to fix it?

We need to **pivot** those columns into a new pair of variables:

```
table4a %>%
 pivot_longer(c(`1999`, `2000`), names_to = "year",
 values to = "cases")
\# # A tibble: 6 x 3
#>
    country year
                    cases
#> <chr> <chr> <int>
#> 1 Afghanistan 1999 745
#> 2 Afghanistan 2000 2666
#> 3 Brazil 1999 37737
#> 4 Brazil 2000 80488
#> 5 China 1999 212258
#> 6 China 2000 213766
```

What is happening here?

We switched from wide to long format:

country	year	cases	country	1999	2000
Afghanistan	1999	745	Afghanistan	745	- 2
Afghanistan	2000	2666	Brazil	37737	804
Brazil	1999	37737	China	212258	213
Brazil	2000	80488			
China	1999	212258			
China	2000	213766		table4	

What else can go wrong?

Datasets where observations are scattered across multiple rows:

```
table2
\# # A tibble: 12 x 4
#>
    country year type
                                count
#> <chr> <int> <chr>
                                <int>
#> 1 Afghanistan 1999 cases
                                 745
#> 2 Afghanistan 1999 population 19987071
#> 3 Afghanistan 2000 cases
                                2666
#> 4 Afghanistan 2000 population 20595360
#> 5 Brazil 1999 cases
                                37737
#> 6 Brazil 1999 population 172006362
#> # ... with 6 more rows
```

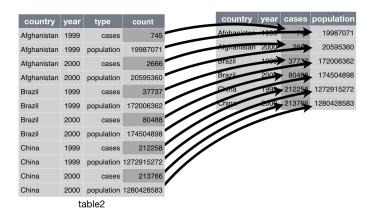
How to fix it?

We need to **pivot** those rows into a new pair of columns:

```
table2 %>%
   pivot wider(names from = type, values from = count)
#> # A tibble: 6 x 4
#> country year cases population
#> <chr> <int> <int>
                              <int>
#> 1 Afghanistan 1999 745 19987071
#> 2 Afghanistan 2000 2666 20595360
#> 3 Brazil 1999 37737 172006362
#> 4 Brazil 2000 80488 174504898
#> 5 China 1999 212258 1272915272
#> 6 China 2000 213766 1280428583
```

What is happening here?

We switched from long to wide format:



Storing tabular data

Common file formats for storing tabular data:

- → Comma-separated values (.csv) ubiquitous and simple
 - → Each *line* is an observation
 - → Each variable value is separated by a comma
- → Application specific (proprietary) formats (.dta, .sav, .xls etc.)
 - → Can allow for richer representations including meta-data
 - → More complex, and not necessarily human-readable
 - → Can have explicit data limits (e.g. see Public Health England's use of .xls spreadsheets)

Often choice is dictated by the source (and size) of the data

→ Packages like haven allow for reading in non-csv formats in R

Be very careful when storing data!

Some good practises for code in (research) projects

Good practices in scientific computing

- → Before we continue with examples of processing tabular data in R, it is helpful to spend some time early in this course with a brief discussion of good coding practises
- → Based on Nagler (1995) "Coding Style and Good Computing Practices" (PS) and Wilson *et al* (2017) "Good Enough Practices in Scientific Computing" (PLOS Comput Biol)

Good practices in scientific computing

Why care?

- → Yourself
 - → Much lower chance of unnoticed bugs
 - → Future self will be grateful: "Yourself from 3 months ago doesn't answer emails"
 - → More efficient research, avoid retracing own steps
- Others
 - → Keep good records of what you did so that others can understand it
 - → **Replication** is a key part of science

Summary of some good practices

- 1. Safe and efficient data management
- 2. Well organised and documented code
- 3. Organised collaboration
- 4. One project = one repository
- 5. Track changes
- 6. Manuscripts as part of the analysis

1. Data management

- → Save raw data as originally generated
- → Create the data you would like to see, e.g.
 - → If possible, open and non-proprietary formats such as .csv
 - → Informative variable names instead of V322
 - → Informative file names that contain metadata: e.g. 05-alaska.csv instead of state5.csv
- → Record all steps used to process data and store intermediate data files if computationally intensive (easier to rerun parts of a data analysis pipeline)
- → Separate data manipulation from data analysis
- → Prepare README with codebook of all variables
- → Periodic backups (or Dropbox, Google Drive, etc.)
- → Sanity checks: Summary statistics after data manipulation

2. Well organised and documented code

- → Number scripts based on execution order
 - → e.g. 01-clean-data.R, 02-recode-variables.R, 03-run-regression.R, 04-produce-figures.R...
- → Write an explanatory note at the start of each script
 - Author, date of last update, purpose, inputs and outputs, other relevant notes

1. Any task you run more than once should be a function (with a

- → Rules of thumb for modular code
 - meaningful name!)
 - 2. Many functions can be relatively short
 - 3. Can separate functions from execution (e.g. in functions.R file and then use source(functions.R) to load functions into current environment
- → Try to keep it simple rather than too clever
- → Add informative comments before blocks of code

3. Organised collaboration

- → Create a README file with an overview of the project: Title, brief description, contact information, structure of folder
- → Shared to-do list with tasks and deadlines
- → Choose one person as corresponding author / point of contact / note taker
- → Split code into multiple scripts to avoid simultaneous edits
- → GitHub, ShareLatex, Overleaf, Google Docs, etc. to collaborate in writing of manuscript

4. One project = one repository

Logical and consistent folder structure:

- → code or src for all scripts
- data for raw data
- → temp for temporary data files
- → output or results for final data files and tables
- → figures or plots for figures produced by scripts
- → manuscript for text of paper
- → docs for any additional documentation

5 & 6. Track changes; producing manuscript

- → Ideally: Use version control (e.g. Git/GitHub)
- → Manual approach: Keep dates versions of code & manuscript, and a changelog file with list of changes
- → Dropbox also has some basic version control built-in
- → Avoid typos and copy&paste errors: Tables and figures can be produced in scripts and compiled directly into manuscript with LATEX

Examples

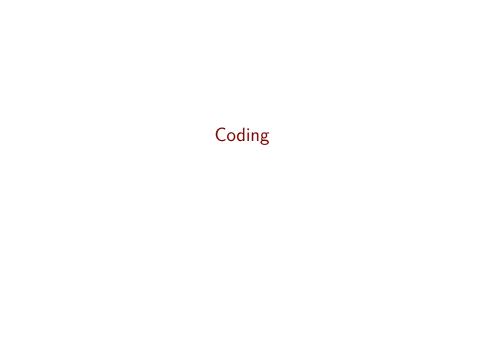
Replication materials for Pablo Barberá's 2014 *Political Analysis* paper:

- → Code on GitHub
- → Code and Data

John Myles White's ProjectTemplate R package.

Another example of replication materials, Thomas Leeper (2017):

→ Code and data



Coding

- → 01-conditionals-loops-functions.Rmd
- → 02-processing-data.Rmd