MY472 – Data for Data Scientists
Week 2: Tabular data

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https://lse-my472.github.io/

Course outline

1. Introduction
2. Tabular data
3. Data visualisation
4. Textual data
5. HTML, CSS, and scraping static websites
6. (Reading week)
7. XML, RSS, and scraping non-static website
8. Working with APIs
9. Creating and managing databases
10. Interacting with online databases
11. Cloud computing

Plan for today

- “Tidy data” and reshaping data in R
- Excursus: Some good practises for code in (research) projects
- Coding

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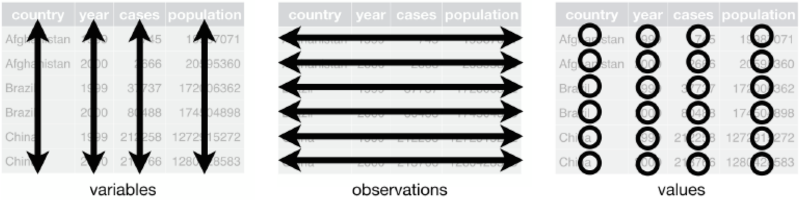
Shapes of data

- 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

“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:

```
table4a
#> # A tibble: 3 x 3
#>   country     `1999` `2000`
#> * <chr>        <int>  <int>
#> 1 Afghanistan    745   2666
#> 2 Brazil       37737  80488
#> 3 China       212258 213766
```

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
Afghanistan	1999	745
Afghanistan	2000	2666
Brazil	1999	37737
Brazil	2000	80488
China	1999	212258
China	2000	213766

country	1999	2000
Afghanistan	745	2666
Brazil	37737	80488
China	212258	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:

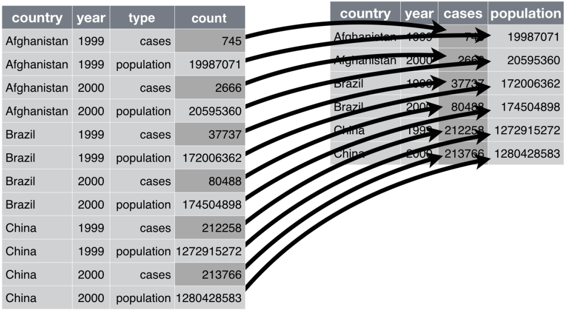


table2

A brief history of reshaping in R

`stats::reshape`: The "classic" method

```
reshape(data, varying = NULL, v.names = NULL, timevar = "time",
        idvar = "id", ids = 1:NROW(data),
        times = seq_along(varying[[1]]),
        drop = NULL, direction, new.row.names = NULL,
        sep = ".",
        split = if (sep == "") {
            list(regexp = "[A-Za-z][0-9]", include = TRUE)
        } else {
            list(regexp = sep, include = FALSE, fixed = TRUE)}
        )
```

A brief history of reshaping (cont.)

reshape2: First update

```
melt(data, ..., na.rm = FALSE, value.name = "value")

## S3 method for class 'data.frame'
melt(data, id.vars, measure.vars,
    variable.name = "variable", ..., na.rm = FALSE,
    value.name = "value", factorsAsStrings = TRUE)

dcast(data, formula, fun.aggregate = NULL, ..., margins = NULL,
      subset = NULL, fill = NULL, drop = TRUE,
      value.var = guess_value(data))
```

A brief history of reshaping (cont.)

tidyr: Current (tidyverse) iteration

```
pivot_longer(
  data,
  cols,
  names_to = "name",
  names_prefix = NULL,
  names_sep = NULL,
  names_pattern = NULL,
  names_ptypes = list(),
  names_transform = list(),
  names_repair = "check_unique",
  values_to = "value",
  values_drop_na = FALSE,
  values_ptypes = list(),
  values_transform = list(),
  ...
)
pivot_wider(
  data,
  id_cols = NULL,
  names_from = name,
  names_prefix = "",
  names_sep = "_",
  names_glue = NULL,
  names_sort = FALSE,
  names_repair = "check_unique",
  values_from = value,
  values_fill = NULL,
  values_fn = NULL,
  ...
)
```

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- 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
- Rules of thumb for modular code
  1. Any task you run more than once should be a function (with a 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

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Coding

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