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

- This week's `git` quick lesson: forking the website
- "Tidy data" and reshaping data in R
- Some good practises for code in (research) projects
- Coding

This week's `git` quick lesson: forking the website

Forking `lse-my472.github.io`

We discussed `git` branches and forks last week

You saw how to create a branch in your own repo

A **fork** is a copy of a repo that is its own repo

- Quite similar to a branch, but it is *not* within the same repo
- Pushed changes to a fork do not affect original remote repo
- Allows you to have a completely separate copy of a repo with your own changes while also pulling changes from the original remote as needed

Let's create a fork of the course website and clone locally

- Creates a copy of all the files in your own repo
- You can pull updates to your local copies every week

Forking `lse-my472.github.io`

1. Go to
   `https://github.com/lse-my472/lse-my472.github.io`
   and click Fork
2. Alter settings (optional) and click Create fork
3. Clone your fork to your computer using the usual process
4. Configure your computer so that it knows where the original remote repo is, and name it `upstream`:

```
git remote add upstream https://github.com/lse-my472/lse-my472.github.io.git
```

Important note: if you want to avoid headaches for now, do not make changes to the local copies of the files on your computer, as this may create merge conflicts

Syncing updates

Whenever you want to get updates (e.g., before lectures and seminars), sync your fork one of two ways

Option 1

1. On your computer, go to the command line, `cd` to your local copy of the fork
2. Fetch the changes from the original remote:
   `git fetch upstream`
3. Check that you're on your `master` branch:
   `git checkout master`
4. Merge the fetched changes from `upstream` into your fork: `git merge upstream/master`

Syncing updates

Whenever you want to get updates (e.g., before lectures and seminars), sync your fork one of two ways

Option 2

1. Go to your fork on GitHub and click "Sync Fork"
2. On your computer, go to the command line, `cd` to your local copy of the fork
3. Then, run `git pull` to bring changes from the GitHub copy of your fork to your local computer's copy

“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

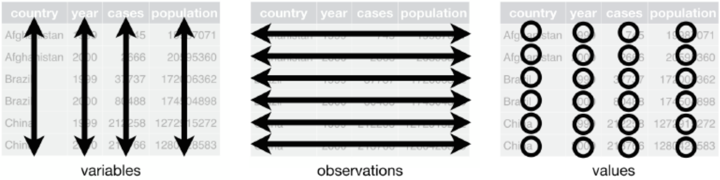
	tweet	tags	lists	list_descriptions
1	I think MY472 is the best course ever	LSE, MY472	asds_tweets, publicity	my thoughts, to share


```
{
    "tweet" : {
        "message" : "I think MY472 is the best course ever",
        "tags" : ["LSE", "MY472"],
        "lists" : [
            {
                "name" : "asds_tweets",
                "description" : "my thoughts"
            },
            {
                "name" : "publicity",
                "description" : "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



Remainder of section based on
https://r4ds.had.co.nz/tidy-data.html

How will we work with "tidy" tabular data in R?

- In this course, we will use the `tidyverse` collection of packages to work with tabular data
- This package contains a bunch of useful tools; it's worth familiarising yourself at https://www.tidyverse.org/
- In the tidyverse, tabular data is stored in a `tibble`
- There are other ways to work with tabular data, e.g. "base R"
  - In base R, tabular data is stored as a `data.frame` or even `matrix`
- We don't care if you'd rather use base R for your own work, but we will mostly use `tidyverse` in class
  - We expect your turned in assignments to replicate whatever `tidyverse` would do

What does “tidy” data look like in R?

Here’s a chunk of an example dataset (as a `tibble`)

```
table1
#> # A tibble: 6 × 4
#>   country      year  cases population
#>   <chr>       <dbl>  <dbl>      <dbl>
#> 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 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
```

(There is another problem beyond the structure of the table. . .)

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
```

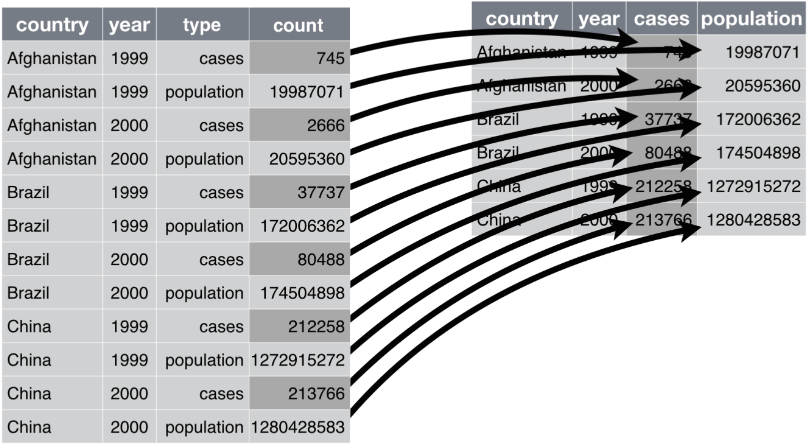
How to fix it?

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:



country	year	type	count
Afghanistan	1999	cases	745
Afghanistan	1999	population	19987071
Afghanistan	2000	cases	2666
Afghanistan	2000	population	20595360
Brazil	1999	cases	37737
Brazil	1999	population	172006362
Brazil	2000	cases	80488
Brazil	2000	population	174504898
China	1999	cases	212258
China	1999	population	1272915272
China	2000	cases	213766
China	2000	population	1280428583

table2

country	year	cases	population
Afghanistan	1999	745	19987071
Afghanistan	2000	2666	20595360
Brazil	1999	37737	172006362
Brazil	2000	80488	174504898
China	1999	212258	1272915272
China	2000	213766	1280428583

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
- 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, 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
  - E.g., tables and figures can be produced in scripts and compiled directly into manuscript with Rmarkdown or LaTeX

Examples

Barberá (2014) (link to paper):

- Replication materials (code and data)
- Code on GitHub

Thomas Leeper (2017) (link to paper):

- Replication materials (code and data)

Copus, Hübert and Pellaton (2024) (link to paper):

- Replication materials (code and data)

Also see John Myles White's ProjectTemplate R package

Coding

Coding

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