Some good practices for research with R

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March 16, 2023

1. Validate our data with {validate}

2. Make our R environment reproducible with {renv}

3. Make our paths reproducible with {here}

4. Keep a clean session

Validate our data with {validate}



Cleaning data can take hundreds or thousands of lines.

Sometimes we do some mistakes that can have **big consequences**.



This is a retraction of: Paola Giuliano, Antonio Spilimbergo, Growing up in a Recession, *The Review of Economic Studies*, Volume 81, Issue 2, April 2014, Pages 787–817, https://doi.org/10.1093/restud/rdt040

The authors and editorial team are retracting this article because the original findings cannot be replicated, likely as a result of an inadvertent coding error. While the original codes and data sets are no longer available, new analysis with a markedly similar data set does not support the original results.

Paper published in the JPE (error found in replication led by I4R):

Note on: Cooperative Property Rights and Development: Evidence from Land Reform in El Salvador

> Eduardo Montero* University of Chicago

> > March 1, 2023

First and foremost, I want to thank Anders Kjelsrud, Andreas Kotsadam, and Ole Rogeberg for their careful and thoughtful replication of Montero (2022). In their replication efforts, documented in Kjelsrud et al. (2023), they uncover a data mistake which affects the results reported in Table 5 and Figure 6 of Montero (2022). This table and figure had presented evidence that land reform cooperatives had lower earnings inequality compared to haciendas. Once the data merging error is corrected, these results are no longer valid. Below I discuss in greater detail the data merging error and, to motivate future research, present an alternative, correlational analysis that explores whether collective ownership is associated with lower inequality using more recent data.

What is {validate}?

{validate} is an R package whose goal is to ensure that our code has produced the expected output.

It should be used on the final and on the intermediate datasets (basically anytime we do some big modifications).

How to use {validate}?

1. Define a series of expectations, or *rules*, with validator()

2. Pass our dataset through these rules with confront()

3. Check that all rules are respected.

Example

Let's take an example with some data:

```
1 head(my_data)
# A tibble: 6 \times 7
                                          pop gdpPercap iso
             continent year lifeExp
  country
  <fct>
             <fct>
                       <int>
                               <dhl>
                                        <int>
                                                  <dbl> <chr>
1 Afghanistan Asia
                        1952
                                28.8
                                                   779. AFG
                                      8425333
2 Afghanistan Asia
                        1957
                                      9240934
                                30.3
                                                   821. AFG
3 Afghanistan Asia
                        1962
                                32.0 10267083
                                                   853. AFG
4 Afghanistan Asia
                        1967
                                34.0 11537966
                                                   836. AFG
5 Afghanistan Asia
                        1972
                                36.1 13079460
                                                   740. AFG
6 Afghanistan Asia
                        1977
                                38.4 14880372
                                                   786. AFG
```

1. Define a series of expectations, or *rules*, with validator():

```
1 library(validate)
2
3 rules <- validator(
4  # Ensure that all ISO-3 codes have 3 letters
5 field_length(iso, n = 3),
6
7  # Ensure that there are no duplicated combination of iso-year
8  is_unique(iso, year),
9
10  # Ensure that year doesn't have any missing values
11 !is.na(year)
12 )</pre>
```

2. Pass our dataset through these rules with confront():

```
1 x <- confront(my_data, rules)</pre>
  x <- summary(x)</pre>
 X
name items passes fails nNA error warning
                                                            expression
     1704
                                      FALSE field_length(iso, n = 3)
              1704
                           0 FALSE
                                                 is_unique(iso, year)
      1704
  V2
              1704
                           0 FALSE
                                      FALSE
                                                          !is.na(year)
  V3
      1704
              1704
                           0 FALSE
                                      FALSE
```

3. Check that all rules are respected (or generate an error if there's a failing test):

1 stopifnot(unique(x\$fails) == 0)

Writing rules can be tedious, for example if we have a list of variables that should be positive (GDP, population, etc.).

Instead of writing var1 >= 0, var2 >= 0, ..., we can use var_group():

```
1 rules <- validator(
2  positive_vars := var_group(lifeExp, pop, gdpPercap),
3  positive_vars >= 0
4 )
5
6 x <- confront(my_data, rules)
7 x <- summary(x)
8
9 head(x)</pre>
```

```
name items passes fails nNA error warning
                                                      expression
1 V2.1 1704
                                    FALSE
                                           lifeExp - 0 >= -1e-08
              1704
                        0 FALSE
2 V2.2 1704
             1704
                      0 0 FALSE
                                   FALSE
                                               pop - 0 >= -1e-08
3 V2.3 1704
                                   FALSE gdpPercap - 0 >= -1e-08
                          0 FALSE
             1704
```

There are a lot of other helpers:

- in_range(): useful for e.g percentages
- field_format() for regular expressions
- is_linear_sequence(): useful to check if there are some gaps in time series
- many others...

See more details in the The Data Validation Cookbook.

Make our R environment reproducible with {renv}

Packages in R

Packages make our life simpler by not having to reinvent the wheel.

But *packages evolve!* Between two versions of a same package:

- functions can be removed or renamed;
- function outputs can change in terms of results or display;
- function arguments can be moved, removed or renamed.

Moreover, packages can disappear if they are not supported anymore.

Personal experience

I did my Master's thesis with R using ~30 packages in total.

Two months later, I couldn't run my code anymore because a package I used to extract some results slightly changed one of its arguments.

→ Two lessons:

- 1. choose our packages wisely: better to use popular and actively developed packages;
- 2. use some tools to keep the version of the packages we used.

Packages in R

Even the most used packages in R can change a lot over the years (e.g tidyverse).

It is **our** responsibility to make sure that our scripts are reproducible. If I take our script 4 years later, I should be able to run it.

Problem: how to deal with evolving packages?

Solution

Take a snapshot of packages version using {renv}.

Idea: create a *lockfile* that contains the version of all the packages we used in a project, as well as their dependencies.

When we give the project to someone else, they will be able to restore it with the exact same package versions.

How does it work?

1. Initialize {renv} whenever we want with init();

2. Work as usual;

3. Run snapshot() from time to time to update the lockfile;

4. If we come back to this project later, or if we share this project, run restore() to get the packages as they were when we used them.

Example

Let's take the example of gapminder again. We import two packages, gapminder and countrycode:

```
1 library(gapminder)
2 library(countrycode)
3
4 gapminder$iso <- countrycode(gapminder$country, "country.name", "iso3c")
5
6 head(gapminder)</pre>
```

```
# A tibble: 6 \times 7
           continent year lifeExp
                                        pop gdpPercap iso
  country
                              <dbl>
                                                <dbl> <chr>
  <fct>
             <fct>
                      <int>
                                      <int>
1 Afghanistan Asia
                       1952
                              28.8 8425333
                                                779. AFG
2 Afghanistan Asia
                       1957
                             30.3 9240934
                                                821. AFG
3 Afghanistan Asia
                                                853. AFG
                       1962
                             32.0 10267083
4 Afghanistan Asia
                                                836. AFG
                       1967
                             34.0 11537966
5 Afghanistan Asia
                       1972
                                                 740. AFG
                              36.1 13079460
6 Afghanistan Asia
                                                 786. AFG
                       1977
                              38.4 14880372
```

1. Initialize {renv} whenever we want with init():

```
1 renv::init()
1 * Initializing project ...
 2 * Discovering package dependencies ... Done!
3 * Copying packages into the cache ... Done!
4 The following package(s) will be updated in the lockfile:
5
7 - R6 [* -> 2.5.1]
8 - base64enc [* -> 0.1-3]
9 - bslib [* -> 0.4.2]
10 - cachem [* -> 1.0.6]
11 - cli [* -> 3.5.0]
12 - countrycode [* -> 1.4.0]
13 - digest [* -> 0.6.31]
14 - ellipsis [* -> 0.3.2]
15 - evaluate [* -> 0.19]
16 - fansi [* -> 1.0.3]
17 - fastmap [* -> 1.1.0]
```

This will create:

- a file called renv.lock
- a folder called renv

→ don't touch these files!

2. Work as usual. Let's import another package:

1 library(dplyr)

1 Error in library(dplyr) : there is no package called 'dplyr'

Hum... weird, dplyr was installed on my laptop.

{renv} creates a sort of "local library" in our project, so we need to reinstall
dplyr first:

1 install.packages("dplyr")

1 library(dplyr)

Now that we imported a new package, let's see the status of {renv}:

```
1 renv::status()
```

3. Run snapshot() from time to time to update the lockfile;

```
1 renv::snapshot()
1 The following package(s) will be updated in the lockfile:
 4 - dplyr [* -> 1.0.10]
5 - generics [* -> 0.1.3]
6 - tidyselect [* -> 1.2.0]
7 - withr [* -> 2.5.0]
8
 Do you want to proceed? [y/N]: Y
 * Lockfile written to 'C:/Users/etienne/Desktop/Divers/good-practices/renv.
```

Good to know

{renv} is not a panacea for reproducibility.

If we use some packages that depend on external software (e.g RSelenium uses Java), {renv} cannot install this software for us.

Learn more about {renv} capabilities and limitations on the package's website.

Make our paths reproducible with {here}

Paths

Absolute path: path that is specific to our computer because it starts *at* the root of a computer.

Ex: "C:/Users/etienne/Desktop/myproject/mydata/WDI"

Relative path: path that is specific to a project because it starts *at the root of the project*.

Ex: "mydata/WDI"

Relative paths in R

Use the package {here}:

• to know the working directory:

```
1 here::here()
[1] "C:/Users/etienne/Desktop/Divers/good-practices"
```

• to use some data, script, etc.:

```
1 mydata <- read.csv(here::here("data/WDI/gapminder.csv"))
```

Relative paths in R

The only path in my script is "data/WDI/gapminder.csv".

Therefore, if I give the folder "good-practices" to someone else:

- the output of here::here() will change because the location of the folder on the computer changed.
- but my code will still run because the path to the data inside the folder didn't change.

Relative paths in R

More advantages:

- {here} will also work if we open the script outside of an RStudio project
- {here} will work on all operating systems (e.g no paths problems because of Windows or Mac).

Get more info on {here} on the package's website.

Keep a clean session

Remove all objects

Last but not least: how do we ensure our code will run in a fresh session on another laptop?

If you already use rm(list = ls()) at the beginning of your script...

... you're wrong

Problem

```
What does rm(list = ls()) do?
```

- rm(): remove a list of objects from the environment
- ls(): list all objects in the environment

So rm(list = ls()) removes all the objects from the environment: datasets, variables, etc.

What about loaded packages? What about options set with options()?

Problem

```
rm(list = ls()) does NOT create a fresh R session. Try it yourself:
    1. load any package, e.g dplyr
    2. use it, e.g filter(iris, Species == "setosa")
    3. run rm(list = ls())
    4. try again filter(iris, Species == "setosa")
```

This will still work, meaning that the package was not unloaded.

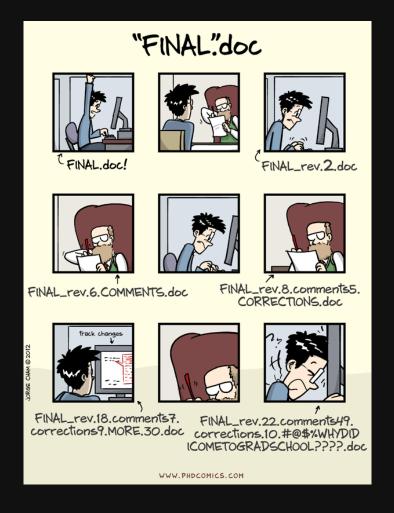
Solution

Instead of using rm(list = ls()), you should completely restart the session to be sure your code can run in a fresh session:

- Session > Restart R;
- or Ctrl + Shift + F10;
- or rstudioapi::restartSession().

Bonus: version control

If this is familiar...



... you should (maybe) use version control!

Version control

Most famous version control tool: Git.

Difference between Git and Github:

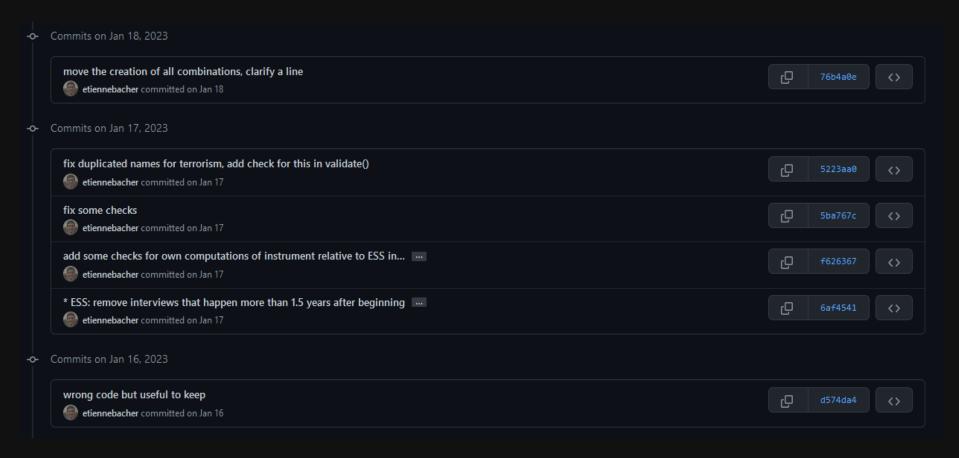
- Git: core tool
- Github: web interface that makes it much easier to use Git

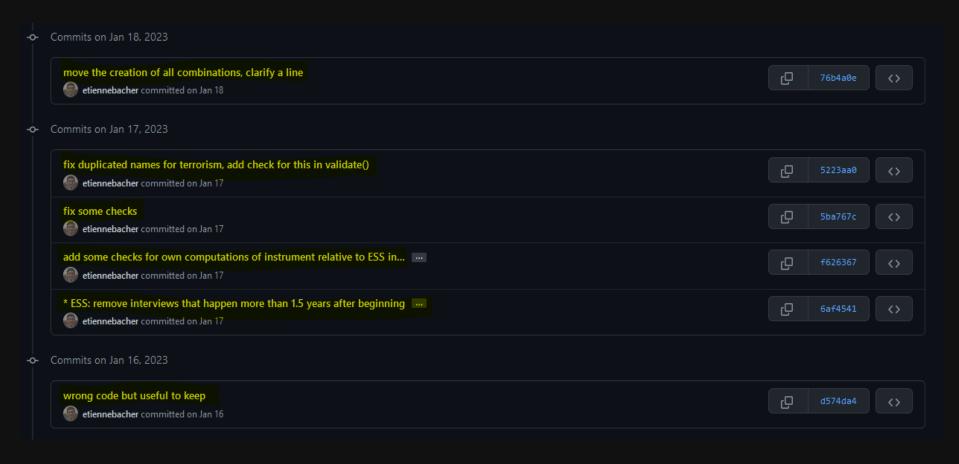
Version control

Idea: you are able to go back to your project at any point in time.

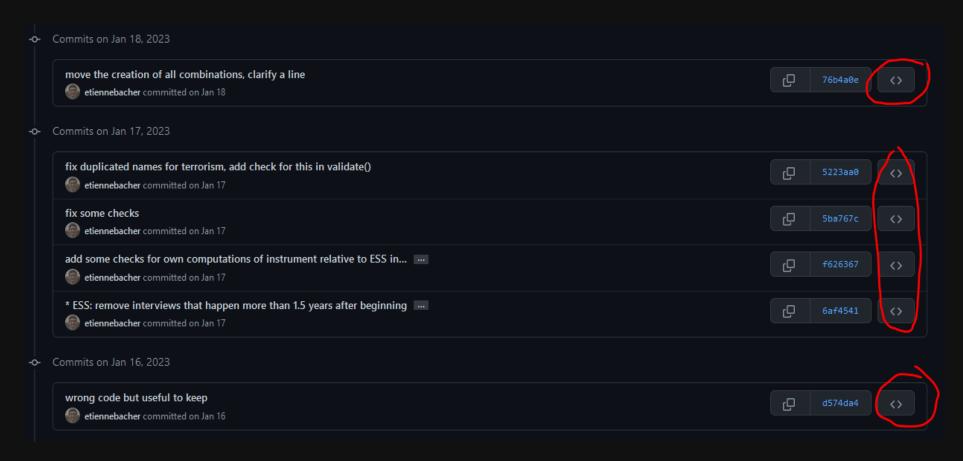
Workflow:

- put your project on a repository
- write code, write drafts, etc.
- once in a while (at the end of the day, or after a big coding session),
 commit and push your changes to the repository
- the repository keeps track of what has changed and allows you to go back to your code at any point in time.





Commits I made: important to add a useful message (unlike some commits here)



Browse the repository when these commits were made (aka time-travel machine).

```
∨ 🐺 45 ■■■■■ Scripts/treat-data.R 📙
         @@ -225,7 +225,9 @@ for (i in unique(ess_total$iso)) {
                x/sum(tmp)*100
                                                                                                                           x/sum(tmp)*100
              })[["1"]]
                                                                                                                          })[["1"]]
              if (is.null(result)) result <- NA
                                                                                                                          if (is.null(result)) result <- NA</pre>
              attitudes_raw[nrow(attitudes_raw) + 1, "iso"] <- i</pre>
                                                                                                                          attitudes_raw[nrow(attitudes_raw) + 1, "iso"] <- i # need nrow + 1 only here</pre>
                                                                                                                                                                             # because it updates
              attitudes raw[nrow(attitudes raw), "year"] <- i
                                                                                                                          attitudes_raw[nrow(attitudes_raw), "year"] <- j</pre>
              attitudes_raw[nrow(attitudes_raw), "measure"] <- k
                                                                                                                          attitudes_raw[nrow(attitudes_raw), "measure"] <- k
              attitudes_raw[nrow(attitudes_raw), "value"] <- result
                                                                                                                          attitudes_raw[nrow(attitudes_raw), "value"] <- result
         @@ -1602,28 +1604,6 @@ tmp_lag <- total_base %>%
        total_base <- left_join(total_base, tmp_lag, by = c("iso_d", "year", to_lag, to_lag2))</pre>
                                                                                                                   total_base <- left_join(total_base, tmp_lag, by = c("iso_d", "year", to_lag, to_lag2))</pre>
      - ### Complete the dataset with all origin-destination-year
        total_base <- total_base %>%
          group_by(origin, destination) %>%
         fill(iso_o, iso_d, contig, comlang_ethno, comlang_off, colony,
               dist, log_dist, diasp_2001, log_diasp_2001, oecd,
               .direction = "updown") %>%
1614 - ungroup() %>%
1617 - group_by(destination, year) %>%
      fill(contains("gdp_ppp"), contains("pop"), contains("n_"), contains("attack"),
               contains("mig_"), general_issue, political_participation,
               labour_market_mobility, education, family_reunion, permanent_residence,
               citizenship, starts_with("state_of"),
               .direction = "updown") %>%
1623 - ungroup()
```

Version control

Git & Github are also very useful for collaboration (if everyone knows how to use it). It is also possible to link Overleaf and Github.

But not easy to learn and takes time to be efficient (maybe a future training?)

Great resource for Git + Github + R: https://happygitwithr.com

Thanks!

Source code for slides and examples:

https://github.com/etiennebacher/good-practices

Comments, typos, etc.:

https://github.com/etiennebacher/good-practices/issues