Best Practices in Computing

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Applied Quantitative Methods II

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Today's goals

- Understand why computing practices matter for research

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- Understand the role of plain text and command line tools

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- Write better R code: functions, checks, and style
- Understand the role of plain text and command line tools
- Deepen your knowledge of version control with Git

Roadmap

Introduction

Project Organization

Writing Better Code

Plain Text and Tools

Version Control with Git

Wrap-up

Why computing practices matter

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- On errors: Bisbee et al. (2022)

You come back to a project after 6 months.

You need to update one figure.

How long does it take you?

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- **Never** one giant script that does everything

Example: workflow_example project

workflow_example/

- Full example: github.com/franvillamil/workflow_example

File naming conventions

Bad	Good
`Final Data.csv`	`data_cleaned.csv`
`Datos educación.csv`	`datos_educacion.csv`
`analysis.R` (which one?)	`01_clean_data.R`
`figure1final2.pdf`	`fig_scatter_income.pdf`
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- Use **descriptive names**: what is in the file, not when you made it

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  - → `doc.tex`: `\input{../analyses/output/table_models}`

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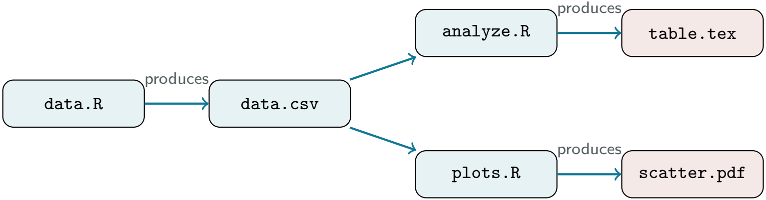
- The document always reflects the latest results

Automating the pipeline: Makefiles

```
all:  create_data/output/data.csv analyses/output/table_models.tex \
    plots/output/scatter.pdf
create_data/output/data.csv:  create_data/data.R
    Rscript --no-save create_data/data.R
analyses/output/table_models.tex:  analyses/analyze.R \
        create_data/output/data.csv
    Rscript --no-save analyses/analyze.R
plots/output/scatter.pdf:  plots/plots.R \
        create_data/output/data.csv
    Rscript --no-save plots/plots.R
```

Note: Makefiles require **tabs** (not spaces) for indentation

Makefiles: the logic



- `make` only re-runs what has **changed**
- The dependency graph ensures correct ordering

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  - → Producing plots with consistent formatting

Define constants at the top

Bad	**Good**
`df = df[df$year >= 2000, ]`	`start_year = 2000`
`...`	`...`
`df2 = df2[df2$year >= 2000, ]`	`df = df[df$year >= start_year, ]`
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- From the example project:
  - → `n_obs = 1000`
  - → Used throughout — change it once to re-run with different sample size

Write checks and assertions

```
# After merging two datasets
merged = merge(df1, df2, by = "id")
if(nrow(merged) != nrow(df1)) {
  stop("Merge changed number of rows!")
}

# Check for duplicates
if(any(duplicated(df$id))) {
  stop("Duplicate IDs found!")
}

# Sanity check on values
if(any(df$age < 0 | df$age > 120, na.rm = TRUE)) {
  warning("Suspicious age values detected")
}
```

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- This is especially valuable when running scripts via `Rscript` or `make`

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- Your code is read more often than it is written

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- The goal: use it for **as much as possible**

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- Terminal on Mac/Linux, Git Bash or WSL on Windows

How do you currently organize your R projects?

One script or many? How do you keep track of output?

Roadmap

- Introduction
- Project Organization
- Writing Better Code
- Plain Text and Tools
- Version Control with Git
- Wrap-up

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- Today: going deeper into **good practices**

The `.gitignore` file

Track (source files):

- R scripts (`.R`)
- LaTeX source (`.tex`)
- Makefiles
- Documentation (`.md`)
- Small data files (`.csv`)

Do NOT track:

- Generated output (`.pdf`, `.png`)
- LaTeX auxiliary files (`.aux`, `.log`)
- Large data files
- System files (`.DS_Store`)
- Sensitive data

```
.gitignore:
*.pdf
*.aux
*.log
.DS_Store
output/
```

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- Your commit history is a **lab notebook**
  - → You should be able to reconstruct what you did and why

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- Your `workflow_example`-style project is already a replication package

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  - → Rare if you communicate and divide tasks well
- Even for solo work: syncing between laptop and desktop

Roadmap

Introduction

Project Organization

Writing Better Code

Plain Text and Tools

Version Control with Git

Wrap-up

Key resources

- Kieran Healy, *The Plain Person's Guide to Plain Text Social Science*:

  → `plain-text.co`

- MIT, *The Missing Semester of Your CS Education*:

  → `missing.csail.mit.edu`

- Software Carpentry lessons (Unix Shell, Git):

  → `software-carpentry.org/lessons`

- Bruno Rodrigues, *Building Reproducible Analytical Pipelines with R*:

  → `raps-with-r.dev`

- Example project: `github.com/franvillamil/workflow_example`

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- **Automate**: use Makefiles to run the pipeline
- **Integrate**: R output feeds directly into LaTeX documents

- **Code well**: DRY, constants at the top, checks and assertions
- **Print diagnostics**: log what your scripts do

- **Use plain text**: portable, versionable, scriptable
- **Use Git**: commit often, write good messages, share via GitHub

For next week

- Complete Assignment 5
- Next session: Panel Data
  - → Fixed effects and within-group variation
  - → The `fixest` package in R

Questions?