Best practices in computing

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Applied Quantitative Methods II

MA in Social Sciences, Spring 2026

Today's goals

- Understand why computing practices matter for research

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- Learn principles for organizing a research project

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- 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

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- The standards of rigor you apply to your theory and research design should extend to your computing

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  - → Running scripts in the wrong order
- **Efficiency**: time invested in workflow saves time later

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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  - → Code transforms raw data into everything else

Organizing a project: one example

```
PROJECT_FOLDER/
├ analyses/
│ ├ analyze.R
│ └ output/
│   └ table_models.tex
├ create_data/
│ ├ data.R
│ └ output/
│   └ data.csv
├ document/
│ ├ doc.tex
│ ├ doc.pdf
│ ├ doc.aux
│ └ ...
├ plots/
│ ├ output/
│ │ └ scatter.pdf
│ └ plots.R
├ Makefile
└ README.md
```

- Full example: github.com/franvillamil/workflow_example

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  - → Delete all output, re-run, and get the same results

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
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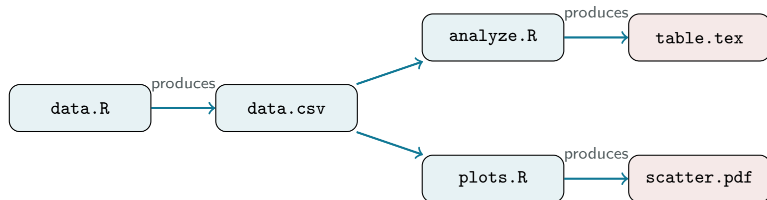
- No local LaTeX? Use **Overleaf** — same `\input{}` workflow

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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  - → Running the same model with different variables
  - → 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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- Not paranoia — this has caused real problems in published work

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- Write **comments** for non-obvious code
  - → Why, not what: `# Drop obs before 1990 (pre-reform)`
  - → Use section dividers: `# ============`
- Your code is read more often than it is written

What NOT to do

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Roadmap

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

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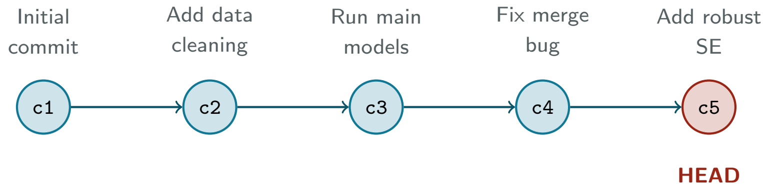
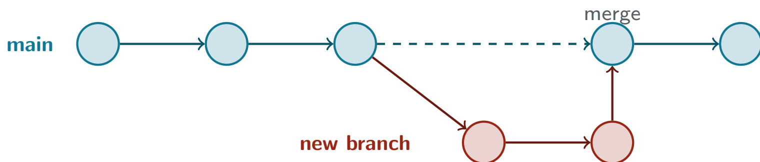
- Today: going deeper into **good practices**

Git: commits as snapshots



- Each **commit** is a snapshot of your project at a point in time
- The **history** is a chain of commits, each with a message
- `HEAD` is a pointer to your current position

Branches: parallel lines of work



- A **branch** is an independent line of commits
- Useful for trying changes without breaking `main`
- **Merge** brings the work back together

The .gitignore file

Track (source files):

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

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

Do NOT track:

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

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  - → You should be able to reconstruct what you did and why

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- Example: `github.com/franvillamil/vox_military`

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- Even for solo work: syncing between laptop and desktop

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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

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

For next week

- Complete Assignment 10 (computing practices)
- Next session: In-class exam + course review
  - → Exam covers sessions 1–9
  - → Second half: review and open questions

Questions?