

# From doing math to writing code

## Workflow and implementation tips

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Thanks to



This talk is about:

- Going from

*“the pseudo-code of the method is given in Algorithm 1”*

to

*“computational results are reported in Table 2”*

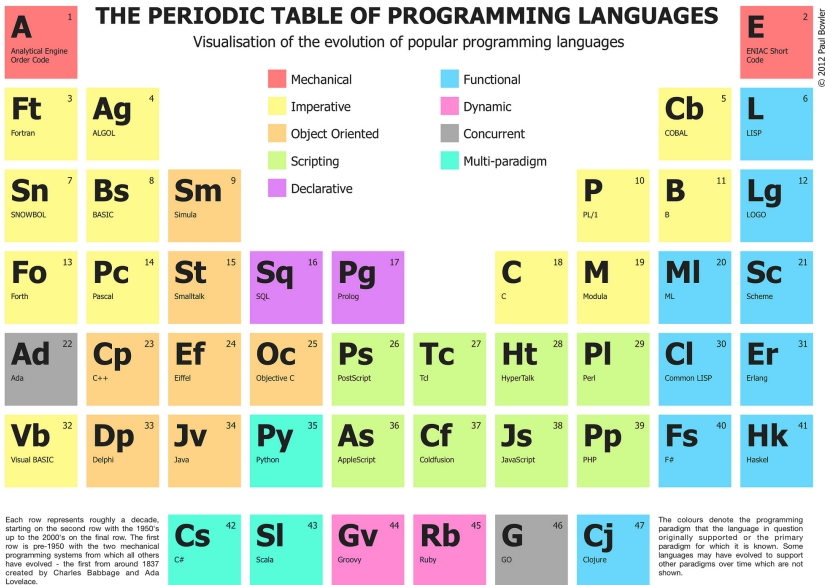
- Making the coding part easier
- Encouraging you to share your code

Material available here: [https://github.com/mtanneau/tutorial\\_airo](https://github.com/mtanneau/tutorial_airo)

# Outline

- 1 Toolset
  - Programming languages
  - Solvers
- 2 Writing code
  - Code structure
  - Style guides
- 3 Version control
  - Version control
  - Git
  - GitHub
- 4 Unit testing
- 5 Running experiments
  - Map-reduce framework
  - Sanity checks
- 6 Conclusion

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## Which programming language?

Some will say it's all about performance vs simplicity...

I find these to be more relevant:

Do you have any hard constraints? (e.g. existing C++ code)

Which language are you most comfortable with?

Would it impair you for the rest of your PhD?

Would it restrict the toolset available to you?

How big is the community?

## Before choosing a solver...

- What kind of problems do you want to solve?
- Do you/your client have a license to use it?
- How easy would it be to change?
- How much of the solver's API do you need?
- Do you really need a *specific* solver?

Helpful link: [Decision-tree for optimization software](#)



## Modelling interfaces go beyond solvers

Sometimes you just want to instantiate a model and solve it, and which solver you use doesn't (really) matter.

That's what modelling languages are for

- :) Focus on the modelling, simpler syntax, solver-agnostic
- :| You may incur some performance cost
- :( You may not have access to all a solver's API (e.g. callbacks)

Many options:

Open-source: [CMPL](#), [CVX](#), [JuMP](#), [PyOmo](#), [YALMIP](#), etc...

Commercial: AMPL, GAMS, AIMMS

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## Base rule

Always separate

**generic code** that can be re-used, from

**specific code** that only makes sense for a given application

and use an `import` to use the generic code.

Why so?

- It is easier to navigate

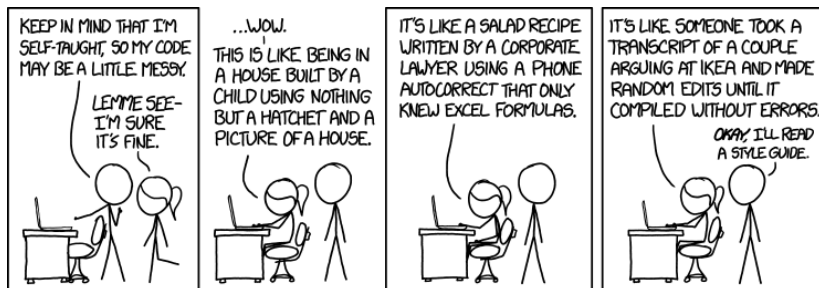
- It allows you to modify one without having to change the other

- Someone (you included) may want to re-use your code later

Typical repository structure:

```
--dat/                                # small data files [optional]
    instance.mps
--doc/                                # documentation
    cholesky.md
    algo.pdf
--examples/                           # illustrative examples
--src/                                # source code (classes and functions)
    --Module1/
    --Module2/
    some_code.jl
--test/                               # unit tests
    runtests.jl
LICENSE                               # code license
README                               # short project description
```

## Write code that other people want to read



How would you write an MILP?

$$\begin{array}{ll} \min_B & \mathcal{X}^T B \\ \text{s.t.} & xB = \mathcal{A}, B \in c \end{array} \quad \text{or} \quad \begin{array}{ll} \min_x & c^T x \\ \text{s.t.} & Ax = b \\ & x \in \mathcal{X} \end{array}$$

We all use *style conventions*, e.g.:

- $x$  is the variable,  $c$  is the objective
- Upper-case denotes matrix, lower-case denotes scalar or vector
- ...

Same applies to code!

Style guide: *"a set of conventions (sometimes arbitrary) about how to write code for that project. It is much easier to understand a large codebase when all the code in it is in a consistent style."* - [Google style guide](#)

Style guides do not make your faster. They make it look nice.

A code with no style guide is like a paper without formatting:  
nobody wants to read it.

Some style guides:

- Python
  - (mandatory) [PEP8](#), [PEP257](#)
  - [Google Python style guide](#)
- C++
  - [Google C++ style guide](#)
- Julia
  - [Julia style guide](#)

A useful tool (for Python): [PyLint](#)

Pick one and stick to it!



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# Version control

What is version control?

Why should I use it?

How do I use it?



## What is version control?

Tracks the evolution of the code

Ensures different people collaborate without conflicting

## Who uses it?

Everyone. And so should you!

See `version_control` notebook

Further resources:

- <https://www.atlassian.com/git/tutorials>
- <https://try.github.io/>
- <https://github.com/ds4dm/tipsntricks/tree/master/git>
- <https://openclassrooms.com/en/courses/3321726-manage-your-code-with-git-and-github>

# Share your code!

Describing an **Algorithm** without **Implementation** is like stating a **Theorem** without **Proof**

**#just\_a\_computational\_conjecture**

- Matteo Fischetti, ISMP2018

Several platforms (free plans available):

- BitBucket: <https://bitbucket.org/>
- GitHub: <https://github.com/>
- GitLab: <https://about.gitlab.com/>

What every paper should have:

*Source code, scripts and data for running the experiments are publicly available at [...]*

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# Unit testing

What is unit testing?

Why you should use it

How to use it in practice





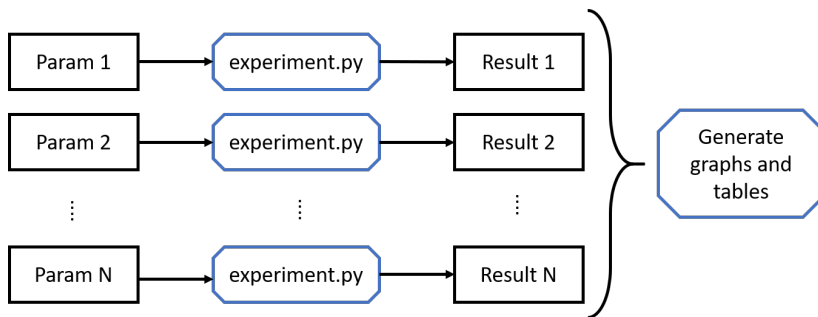
## Demo

## Unit tests in practice

- ① Always write tests for your source code!
- ② Run tests locally before making a commit
- ③ Continuous integration
  - Automatically run tests when modifications are pushed
  - Free for open-source projects
- ④ Unit tests do not prevent bugs (but they help)!
- ⑤ Most useful at later stages of your project (prevent breaks)

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Numerical experiments typically look like



## The "atomic experiment" (a.k.a, a job)

```
$ python experiment.py --arg1 p1 --arg2 p2 > output_p1_p2.txt
```

```
run experiment.py
```

with arguments `arg1=p1` and `arg2=p2`

and redirect output to `output_p1_p2.txt`

### Examples:

- Process a given data file
- Read an instance from a file and solve it
- Train a ML model with given hyperparameters

## Example workflow for running experiments

- 1 Generate the list of jobs

```
python test_preprocess.py > jobs.txt
```

- 2 Launch jobs

```
cat jobs.txt | parallel -j 4
```

(remember to re-launch if failures)

- 3 Generate graphs and tables

```
python test_postprocess.py
```

## Sanity checks

- Use random seeds and save them (either as parameter or output)
- Check that you do output the data you need to output
- Do not run the same job twice
- Generate graphs/tables without having to re-run all jobs
- Watch out for disk space (data files, large outputs)
- Don't run more jobs than you have cores
- Check that everything runs as intended
- Ensure you can map results back to a job's parameters!

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## Wrapping-up:

- Use tools you're comfortable with
- Write code that other people want to read
- Use version control
- Seriously, use version control
- Get into the habit of unit tests
- Optimize your code intelligently
- Automate most of your experiments

Share your code! ;)

Thanks! Questions?

