

Reproducible Computational Science with Popper Workflows

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Common Reproducibility Issues (1)

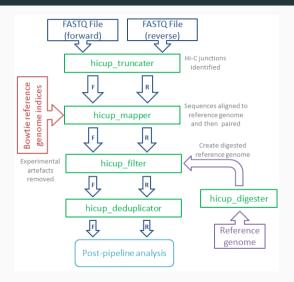


Python statistics libraries

- Research using statistical and/or machine learning tools depends on increasingly complex software stacks
- Replicating a result is difficult due to incomplete dependencies, platform incompatibilities, . . .



Common Reproducibility Issues (2)



- Data processing pipelines have many interdependant steps from the raw data to the final result
- Replicating a workflow requires difficult guesswork if these steps not properly documented



A bioinformatics data pipeline



Popper is a container-native workflow execution engine which addresses these issues:

- Containerizing workflows avoids problems due to different software environments
- Specifying steps explicitely in a Popper workflow file avoids problems due to data pipeline complexity



Limitations

However ...

- Popper requires fluency in DevOps tools (in particular container engines)
- Steep learning curve for users with no prior experience in these tools, who would nonetheless benefit from more reproducible workflows
- ightarrow My goal was to create a collection of tools and tutorials to smooth out this learning curve for users in computational fields



Contributions: Tutorials

Tutorial for developing Popper workflows oriented to Python and R users:

- Computational notebooks with Popper
- Dependency management
- Project structure



Contributions: Templates

cookiecutter templates to bootstrap Popper workflows in Python and R including starter Docker images

```
├─ LICENSE
— REΔDME.md
                                 <- The top-level README.
— data
                                 <- Data used in workflow.
                                 <- Generated paper as PDF, LaTeX.
— paper

— wf.vml

                                <- Workflow starter
                           c- Definitions of containers used in workflow
- containers

    ⊢ exploration

                         <- Container used for exploratory work.
       - exploration.dockerfile <- Default dockerfile used in workflow.
       exploration env.yml <- Defines conda environment used by container.</p>
- results
                              <- Model predictions, serialized models, etc.</p>
   - models
   └─ figures
                                <- Graphics created during workflow.
                                 <- Source code for this project.
L src

─ notebooks

                                 <- Jupyter notebooks.
                                 <- Scripts to download or generate data.
   ├─ data
                                 <- Scripts used to generate models.
   - models
   - figures
                                 <- Scripts to generate graphics.
```

Structure generated by cookiecutter for Python workflows



Contributions: Sample Workflows



Sample Popper workflows in Python and R demonstrating an end-to-end machine learning project with data acquisition and transformation, model fitting and evaluation

Workflow diagram generated by Popper



Highlights (1)

- Key idea in DevOps: minimize the distance between development and production environments
- Users in computational research should be able to develop from the beginning their workflows in Popper
- This is done using Popper's interactive execution feature



Highlights (2)



- Users in computational fields use computational notebooks to prototype workflows
- I added configuration options to the core popper CLI to support running a computational notebook server



Thank you!

I'd like to thank Ivo Jimenez for his mentorship this summer!

