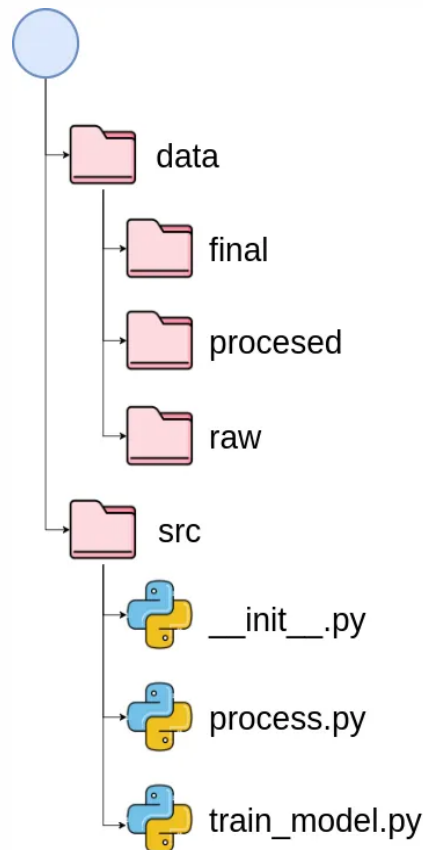
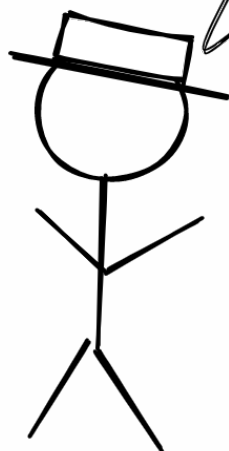
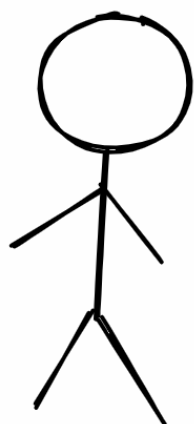


How to Structure an ML Project for Reproducibility and Maintainability

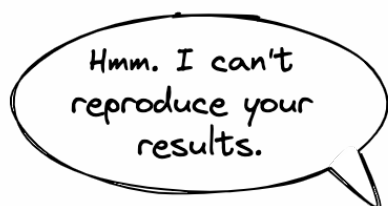
Motivation

Getting started is often the most challenging part when building ML projects. How should you structure your repository? Which standards should you follow? Will your teammates be able to reproduce the results of your experimentations?

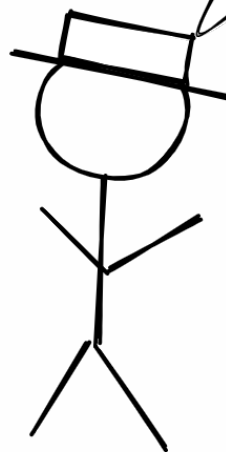
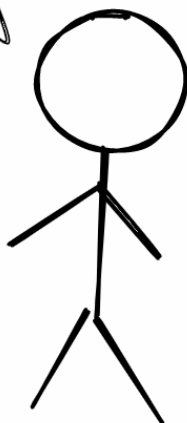




My model has a
0.99 accuracy

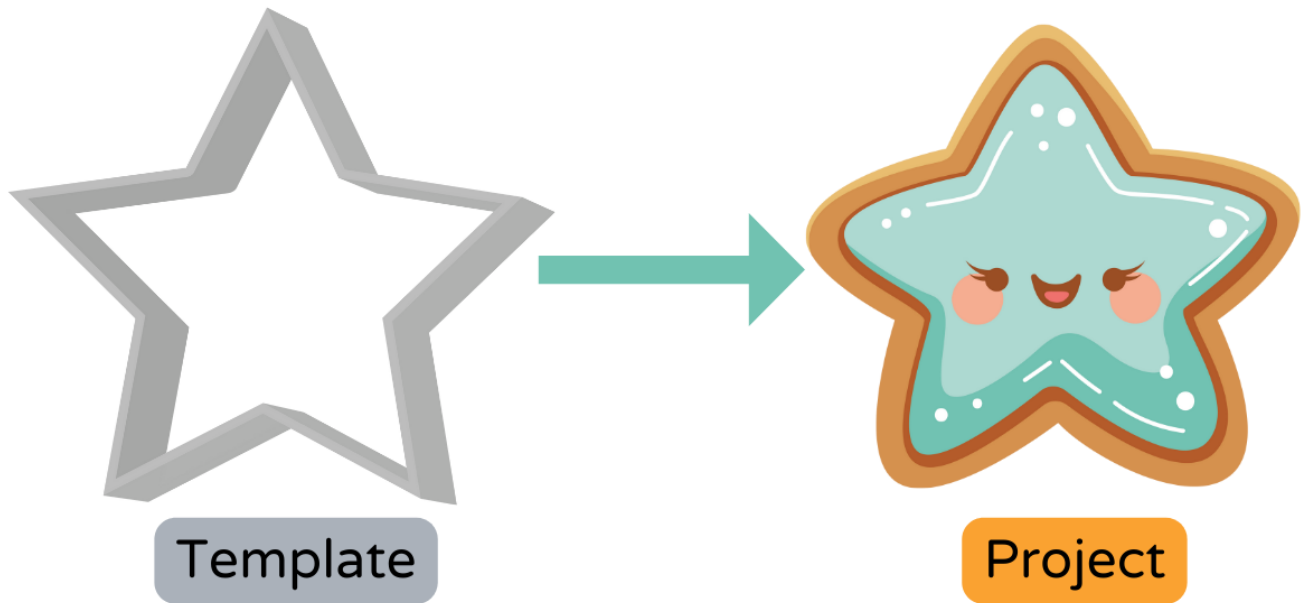


Hmm. I can't
reproduce your
results.



Have you added a dash
of unicorn hair and a pinch of
leprechaun dust
to the data?

Instead of trying to find an ideal repository structure, wouldn't it be nice to have a template to get started?



That is why I created [data-science-template](#), consolidating best practices I've learned over the years about structuring data science projects.

This template allows you to:

- ✓ Create a readable structure for your project
- ✓ Efficiently manage dependencies in your project
- ✓ Create short and readable commands for repeatable tasks
- ✓ Rerun only modified components of a pipeline
- ✓ Observe and automate your code
- ✓ Enforce type hints at runtime
- ✓ Check issues in your code before committing
- ✓ Automatically document your code
- ✓ Automatically run tests when committing your code

Tools Used in This Template

This template is lightweight and uses only tools that can generalize to various use cases. Those tools are:

- [Poetry](#): manage Python dependencies
- [Prefect](#): orchestrate and observe your data pipeline
- [Pydantic](#): validate data using Python type annotations
- [pre-commit plugins](#): ensure your code is well-formatted, tested, and documented, following best practices
- [Makefile](#): automate repeatable tasks using short commands
- [GitHub Actions](#): automate your CI/CD pipeline
- [pdoc](#): automatically create API documentation for your project

Usage

To download the template, start by installing [Cookiecutter](#):

```
pip install cookiecutter
```

Create a project based on the template:

```
cookiecutter https://github.com/khuyentran1401/data-  
science-template
```

Try out the project by following [these instructions](#).

In the following few sections, we will detail some valuable features of this template.

Create a Readable Structure

The structure of the project created from the template is standardized and easy to understand.

Here is the summary of the roles of these files:

```

├── data
│   ├── final                # data after training the
model                         # data after processing
│   ├── processed            # raw data
│   └── raw                  # documentation for your
├── docs                     # configuration for code
project                      # ignore files that cannot
├── .flake8                  commit to Git
formatter
├── .gitignore
├── Makefile                 # store commands to set up
                             the environment
├── models                   # store models
├── notebooks                # store notebooks
├── .pre-commit-config.yaml  # configurations for pre-
commit
├── pyproject.toml           # dependencies for poetry
├── README.md                # describe your project
├── src                      # store source code
│   └── __init__.py          # make src a Python module
```

```
|   |— config.py           # store configs
|   |— process.py         # process data before
training model
|   |— run_notebook.py    # run notebook
|   |— train_model.py     # train model
|— tests                  # store tests
   |— __init__.py         # make tests a Python
module
   |— test_process.py     # test functions for
process.py
   |— test_train_model.py # test functions for
train_model.py
```


Efficiently Manage Dependencies

Poetry is a Python dependency management tool and is an alternative to pip.

With Poetry, you can:

- Separate the main dependencies and the sub-dependencies into two separate files (instead of storing all dependencies in requirements.txt)
- Remove all unused sub-dependencies when removing a library
- Avoid installing new packages that conflict with the existing packages
- Package your project in several lines of code

and more.

Find the instruction on how to install Poetry [here](#).

Create Short Commands for Repeatable Tasks

Makefile allows you to create short and readable commands for tasks. You can use Makefile to automate tasks such as setting up the environment:

```
initialize_git:
    @echo "Initializing git..."
    git init

install:
    @echo "Installing..."
    poetry install
    poetry run pre-commit install

activate:
    @echo "Activating virtual environment"
    poetry shell

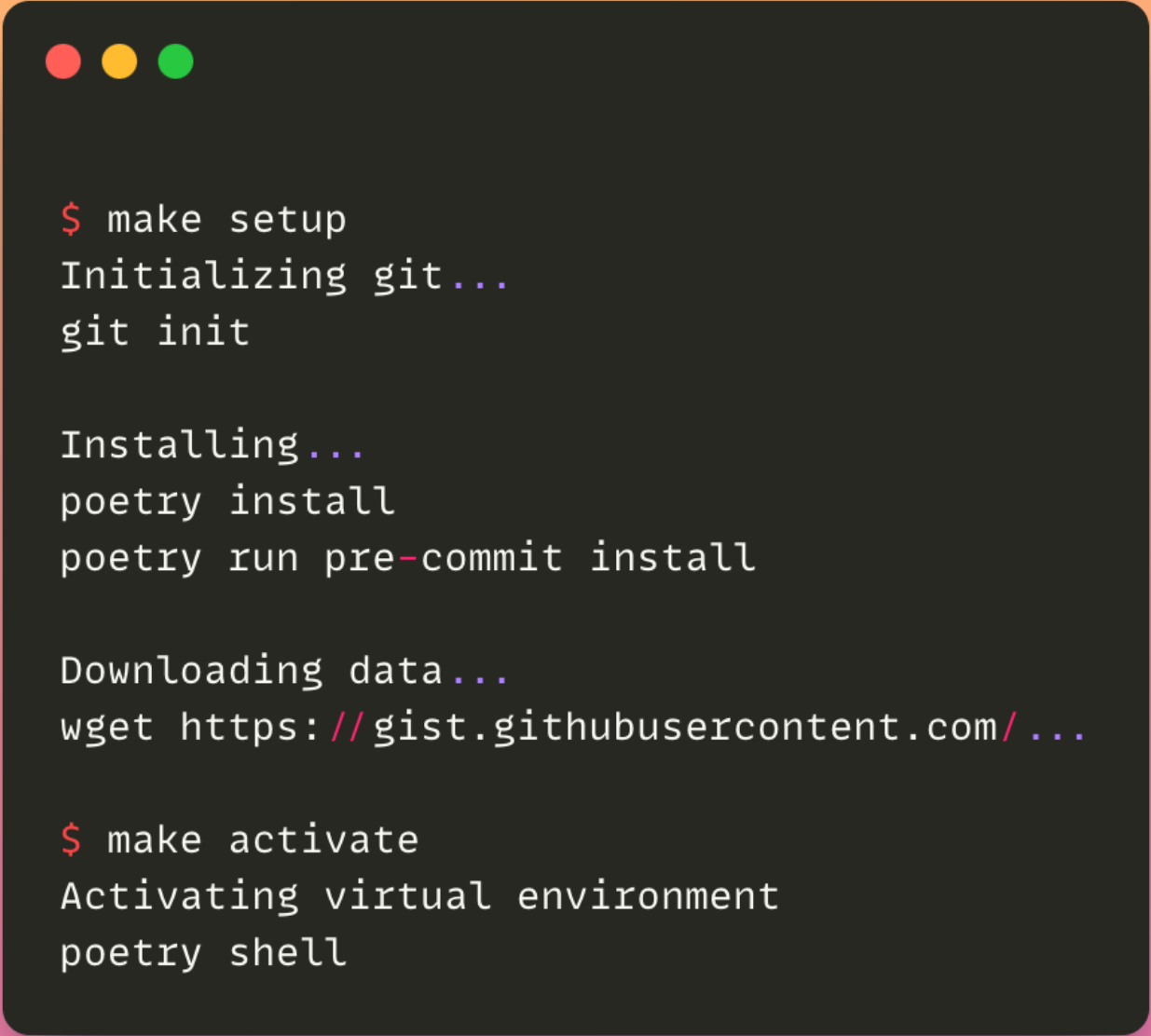
download_data:
    @echo "Downloading data..."
    wget
    https://gist.githubusercontent.com/khuyentran1401/a1abde0a
    7d27d31c7dd08f34a2c29d8f/raw/da2b0f2c9743e102b9dfa6cd75e94
    708d01640c9/Iris.csv -O data/raw/iris.csv

setup: initialize_git install download_data
```

Now, whenever others want to set up the environment for your projects, they just need to run the following:

```
make setup  
make activate
```

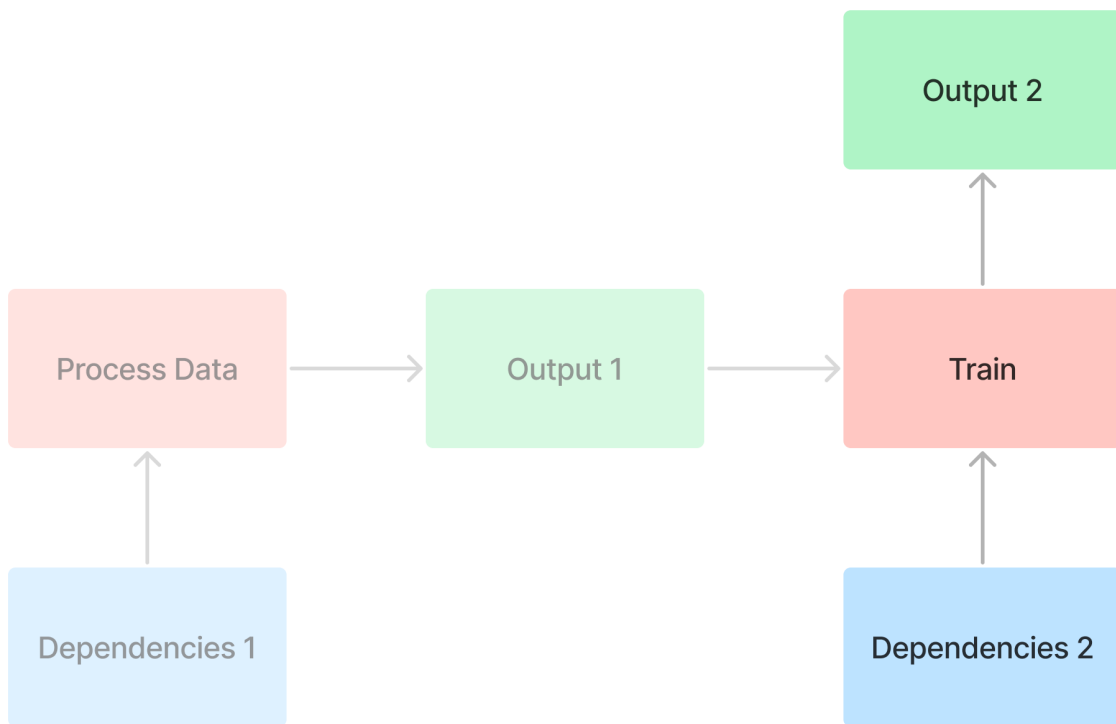
And a series of commands will be run! View the full Makefile [here](#).



```
$ make setup  
Initializing git...  
git init  
  
Installing...  
poetry install  
poetry run pre-commit install  
  
Downloading data...  
wget https://gist.githubusercontent.com/...  
  
$ make activate  
Activating virtual environment  
poetry shell
```

Rerun Only Modified Components of a Pipeline

Make is also useful when you want to run a task whenever its dependencies are modified.

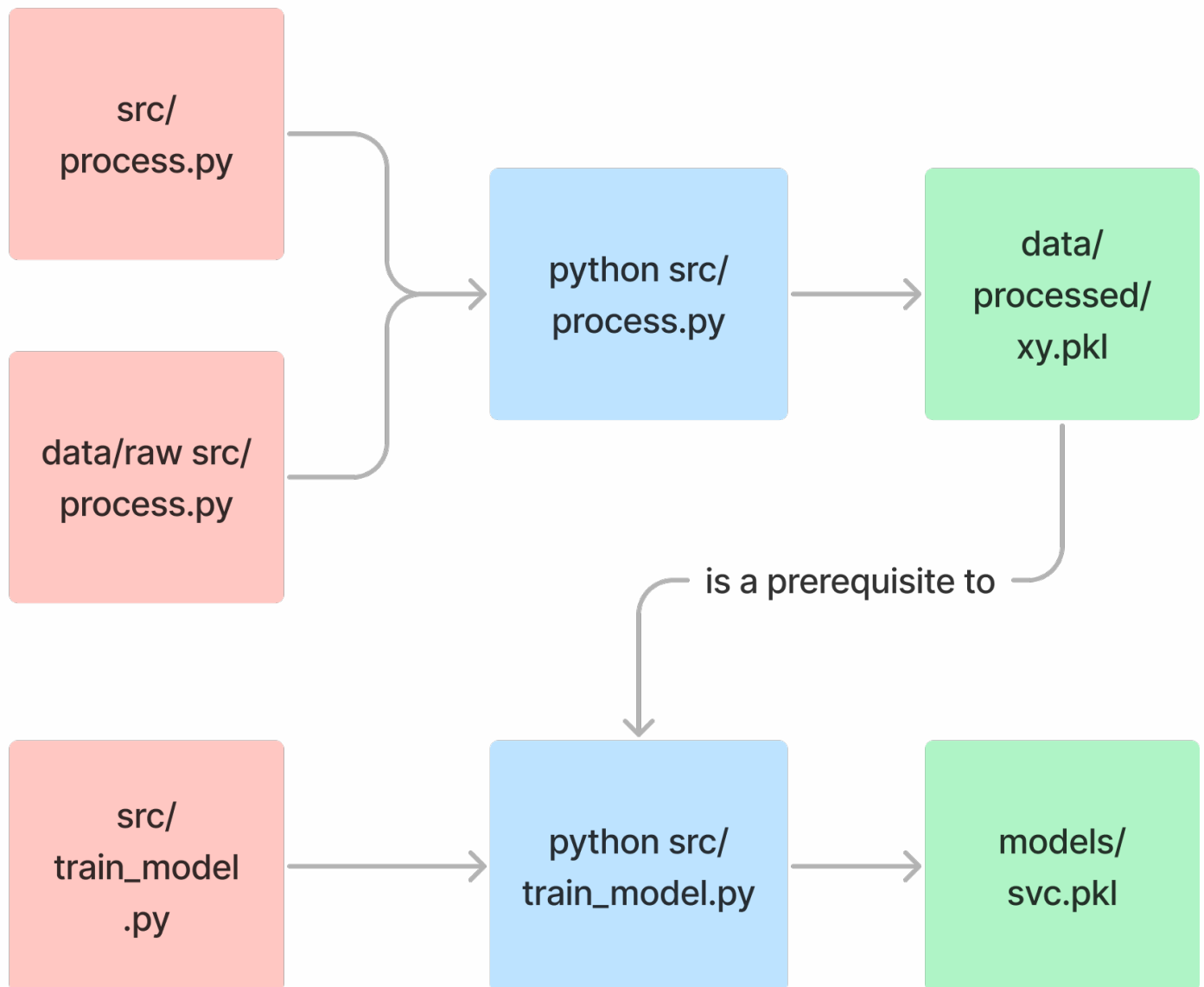


As an example, let's capture the connection between files in the following diagram through a Makefile:

Prerequisites

Recipe

Target



```
data/processed/xy.pkl: data/raw src/process.py
    @echo "Processing data..."
    python src/process.py

models/svc.pkl: data/processed/xy.pkl src/train_model.py
    @echo "Training model..."
    python src/train_model.py

pipeline: data/processed/xy.pkl models/svc.pk
```

To create the file `models/svc.pkl` , you can run:

```
make models/svc.pkl
```

Since `data/processed/xy.pkl` and `src/train_model.py` are the prerequisites of the `models/svc.pkl` target, `make` runs the recipes to create both `data/processed/xy.pkl` and `models/svc.pkl` .

```
Processing data...
python src/process.py

Training model...
python src/train_model.py
```

If there are no changes in the prerequisite of `models/svc.pkl`, `make` will skip updating `models/svc.pkl` .

```
$ make models/svc.pkl
make: `models/svc.pkl' is up to date.
```

Observe and Automate Your Code

This template leverages [Prefect](#) to:

- Observe all your runs from the [Prefect UI](#).

Flow Runs

Flows

Deployments

Work Queues

Blocks

Notifications

Automations

Task Run Concurrency

Flow Runs

Default view



Date Range

01/01/2023 → 01/09/2023



States

All run states



Flows

All flows

Deployments

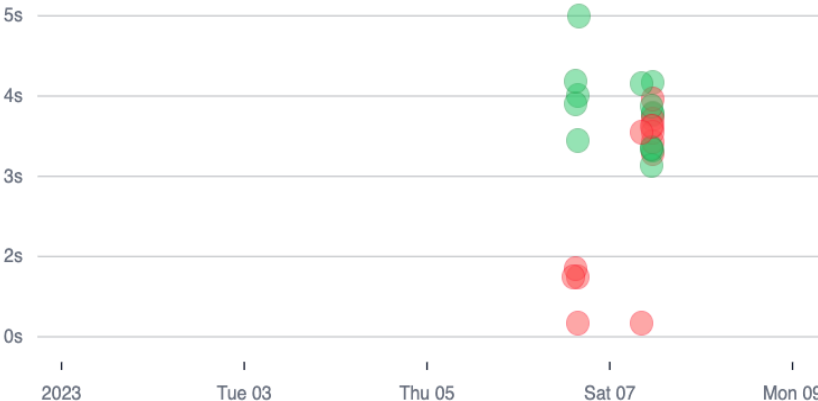
All deployments

Work Queues

All work queues

Tags

All tags



27 Flow runs

Search by flow run name

Newest to oldest

run-notebook > quaint-lyrebird

Completed

2023/01/07 11:22:23 AM

4s

2 task runs

run-notebook > successful-goldfish

Completed

2023/01/07 11:21:57 AM

4s

2 task runs

train > large-lynx

Completed

2023/01/07 11:21:51 AM

4s

5 task runs

run-notebook > malachite-stingray

Failed

2023/01/07 11:21:34 AM

4s

1 task run

Among others, Prefect can help you:

- Retry when your code fails
- Schedule your code run
- Send notifications when your flow fails

You can access these features by simply turning your function into a Prefect [flow](#).

```
from prefect import flow

@flow
def process(
    location: Location = Location(),
    config: ProcessConfig = ProcessConfig(),
):
    ...
```

Enforce Type Hints At Runtime

[Pydantic](#) is a Python library for data validation by leveraging type annotations.

[Pydantic models](#) enforce data types on flow parameters and validate their values when a flow run is executed.



```
from pydantic import BaseModel
```

```
class ProcessConfig(BaseModel):  
    drop_columns: List[str] = ["Id"]  
    label: str = "Species"  
    test_size: float = 0.3
```

```
@flow
```

```
def process(  
    location: Location = Location(),  
    drop_columns: List[str] = ["Id"],  
    label: str = "Species",  
    test_size: float = 0.3,  
):  
    ...
```

If the value of a field doesn't match the type annotation, you will get an error at runtime:

```
process(config=ProcessConfig(test_size='a'))  
  
pydantic.error_wrappers.ValidationError: 1 validation  
error for ProcessConfig  
test_size  
  value is not a valid float (type=type_error.float)
```

All Pydantic models are in [the src/config.py file](#).

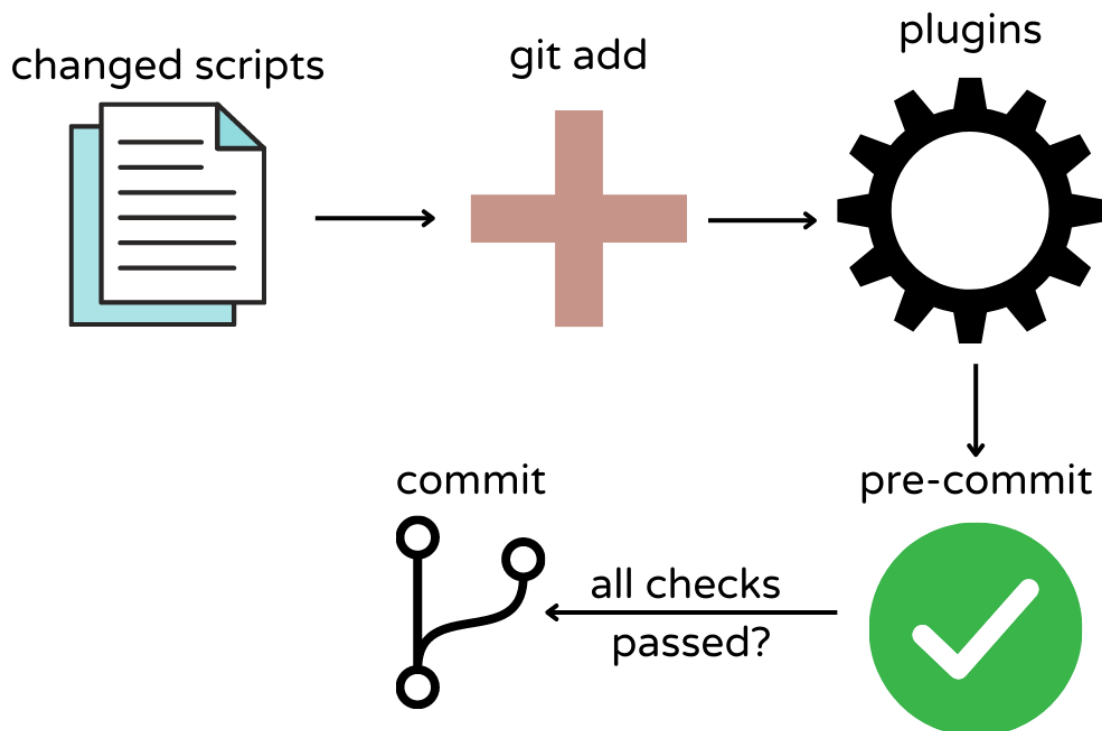
Detect Issues in Your Code Before Committing

Before committing your Python code to Git, you need to make sure your code:

- passes unit tests
- is organized
- conforms to best practices and style guides
- is documented

However, manually checking these criteria before committing your code can be tedious. [pre-commit](#) is a framework that allows you to identify issues in your code before committing it.

You can add different plugins to your pre-commit pipeline. Once your files are committed, they will be validated against these plugins. Unless all checks pass, no code will be committed.



You can find all plugins used in this template in [this .pre-commit-config.yaml file](#).

black



format code

flake8



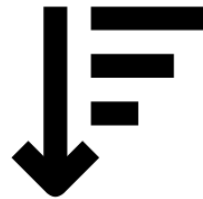
check pep8

interrogate



check docstrings

isort



sort imports

Automatically Document Your Code

Data scientists often collaborate with other team members on a project. Thus, it is essential to create good documentation for the project.

To create API documentation based on docstrings of your Python files and objects, run:

```
make docs_view
```

Output:

```
Save the output to docs...
pdoc src --http localhost:8080
Starting pdoc server on localhost:8080
pdoc server ready at http://localhost:8080
```

Now you can view the documentation on <http://localhost:8080>.

Automatically Run Tests

[GitHub Actions](#) allows you to automate your CI/CD pipelines, making it faster to build, test, and deploy your code.

When creating a pull request on GitHub, the tests in your tests folder will [automatically run](#).

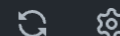
← Test code and app

✓ delete dvc, add docstring, and add makefile #8



✓ Test processed code and model ▾

Test processed code and model



succeeded 15 hours ago in 2m 9s

>	✓ Set up job	2s
>	✓ Checkout	1s
>	✓ Environment setup	0s
>	✓ Install Poetry	22s
>	✓ Install packages	1m 33s
>	✓ Run tests	7s
>	✓ Post Environment setup	0s
>	✓ Post Checkout	0s
>	✓ Complete job	0s

[View the code for this workflow.](#)

Conclusion

Congratulations! You have just learned how to use a template to create a reusable and maintainable ML project. This template is meant to be flexible. Feel free to adjust the project based on your applications.