Efficient Deep Learning Systems

Experiment management & ML code testing

Max Ryabinin

2023

Teaser

ML Code = { Modeling, experiments; Offline quality evaluation; Data preprocessing; Code/model efficiency }

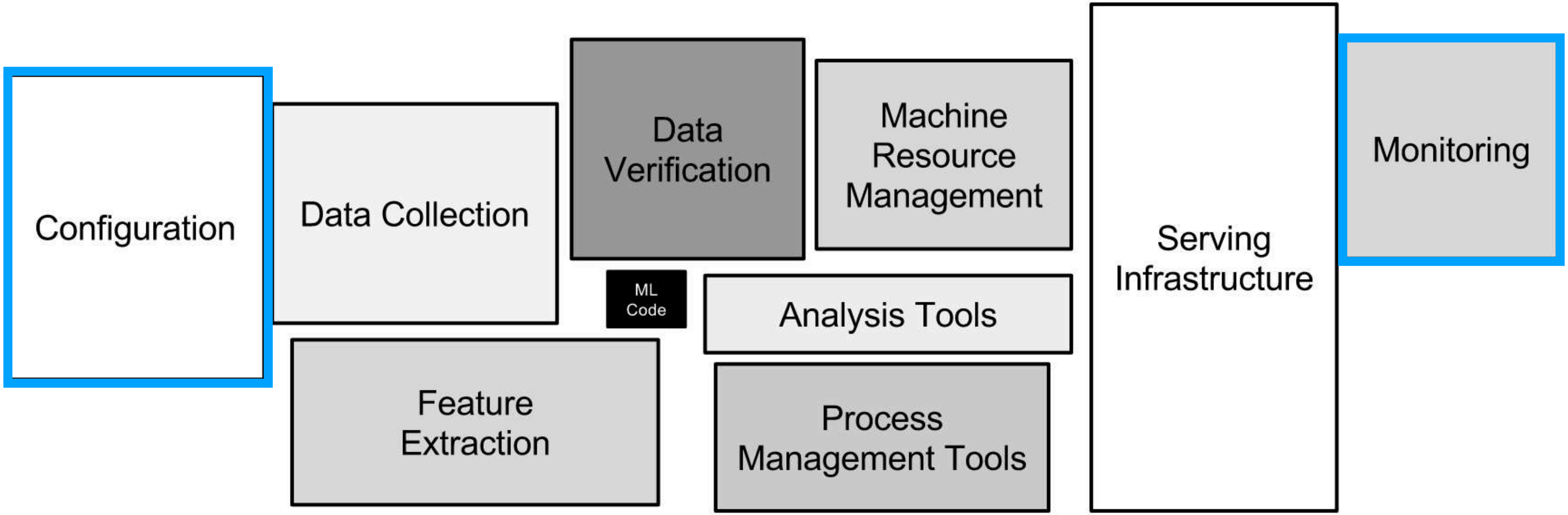
Modeling, experiments

Offline quality evaluation

Data preprocessing

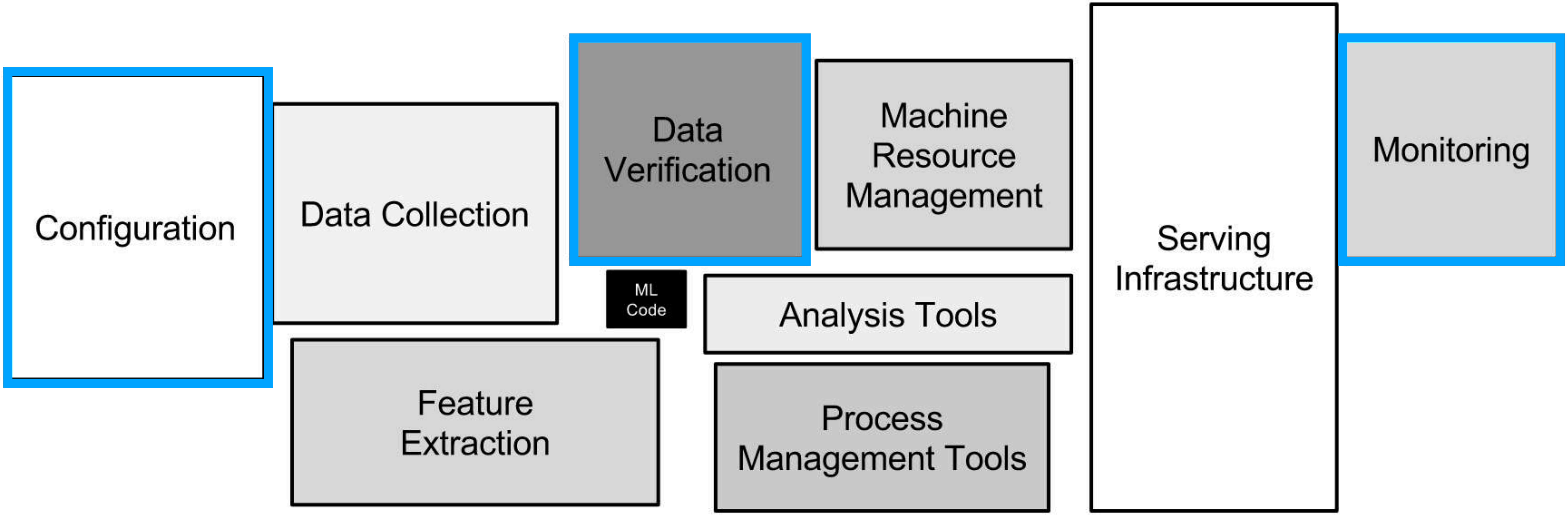
Code/model efficiency

Teaser



“Hidden Technical Debt in Machine Learning Systems”. Sculley et al., NeurIPS 2015

Teaser



“Hidden Technical Debt in Machine Learning Systems”. Sculley et al., NeurIPS 2015

Plan for today

- How (and why) to track your DL experiments
- Versioning your data and models along with the code
- Flexible configuration of Python code
- Testing in general and for ML purposes

Tracking experiments: motivation

- Usually, training a model once is not enough:
  - The data gets updated
  - Hyperparameters need tuning
  - We want to modify the training code for better quality
- For all these cases, we need a way to keep track of our experiments
- Even more important in a <u>collaborative</u> setup

What to track

- Obviously, we want a table with run IDs and final metrics
- What else?
    - Plots with per-step/per-second metrics (convergence & perf)
    - Git commit hash for reproducibility (and diff for local changes!)
    - Visualizations of model inputs/outputs
    - Stdout/stderr of your training script (invest time in good logs)
    - In some cases, full info about the environment

How to track

- There are many tools for this [1,2,3,4,5]
- Range from “just upload the logs” to full-fledged tracking of the entire environment
- Self-hosted versions are available

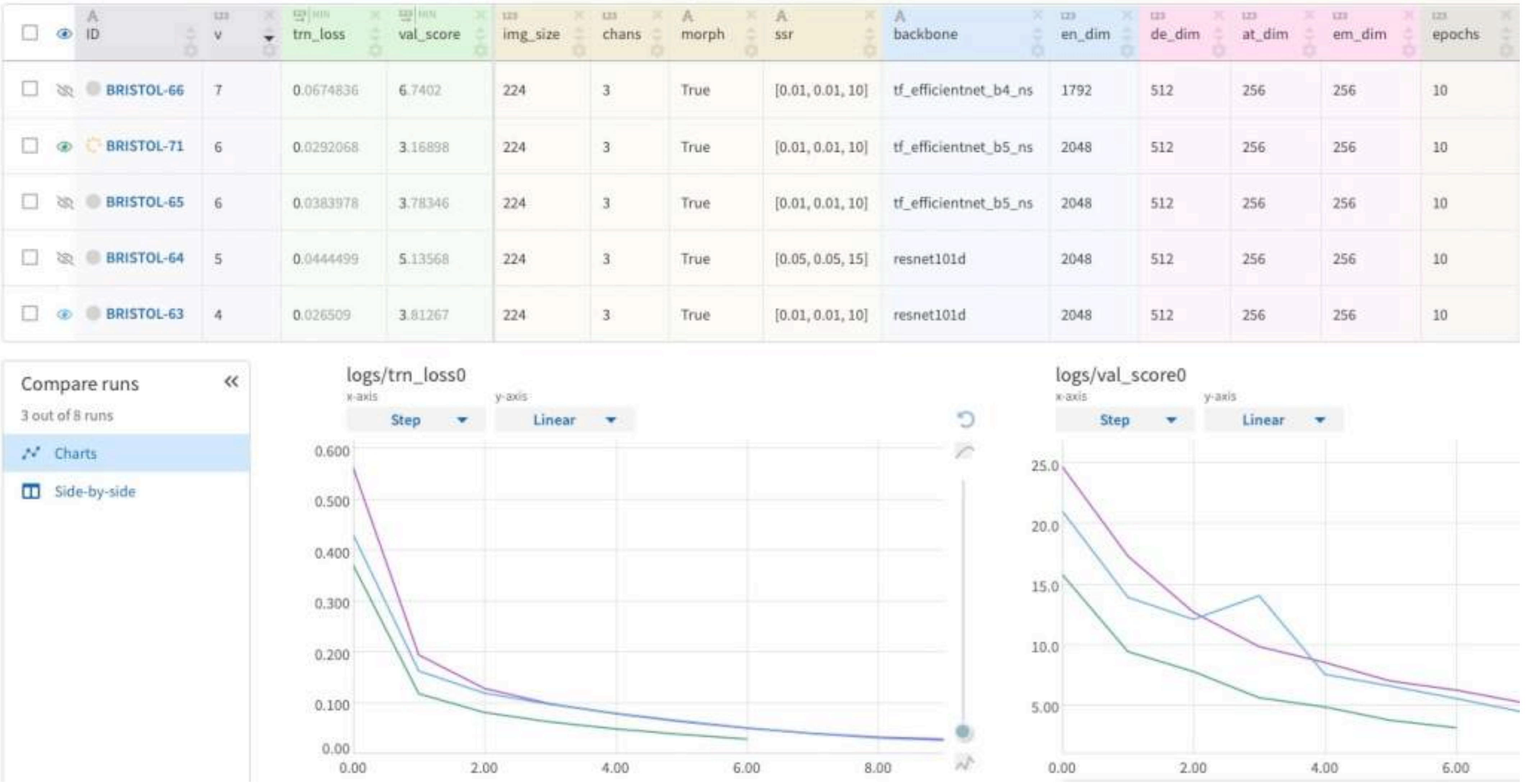


TABLE VIEW | PARALLEL COORDINATES VIEW | SCATTER PLOT MATRIX VIEW

Trial ID	Show Metrics	model	accuracy_test	lr	train_loss
1b2758da0f912...	☐	ViT-L_32	0.82009	1.9467e-10	0.42093
606b401e6f84...	☐	ViT-B_16	0.84609	1.9467e-10	1.0754
60c54527f120...	☐	ViT-L_16	0.85066	1.9467e-10	0.65612
6c5951c20e95...	☐	ViT-B_32	0.81788	1.9467e-10	1.3841
85c586a058ca...	☐	ViT-B_16	0.84621	1.9467e-10	0.45114
a2316e5f8b991...	☐	ViT-L_16	0.85050	1.9467e-10	0.40394
c32186203a97...	☐	ViT-B_32	0.81790	1.9467e-10	1.4536
f853f3481c8db...	☐	ViT-L_32	0.81780	1.9467e-10	0.81554

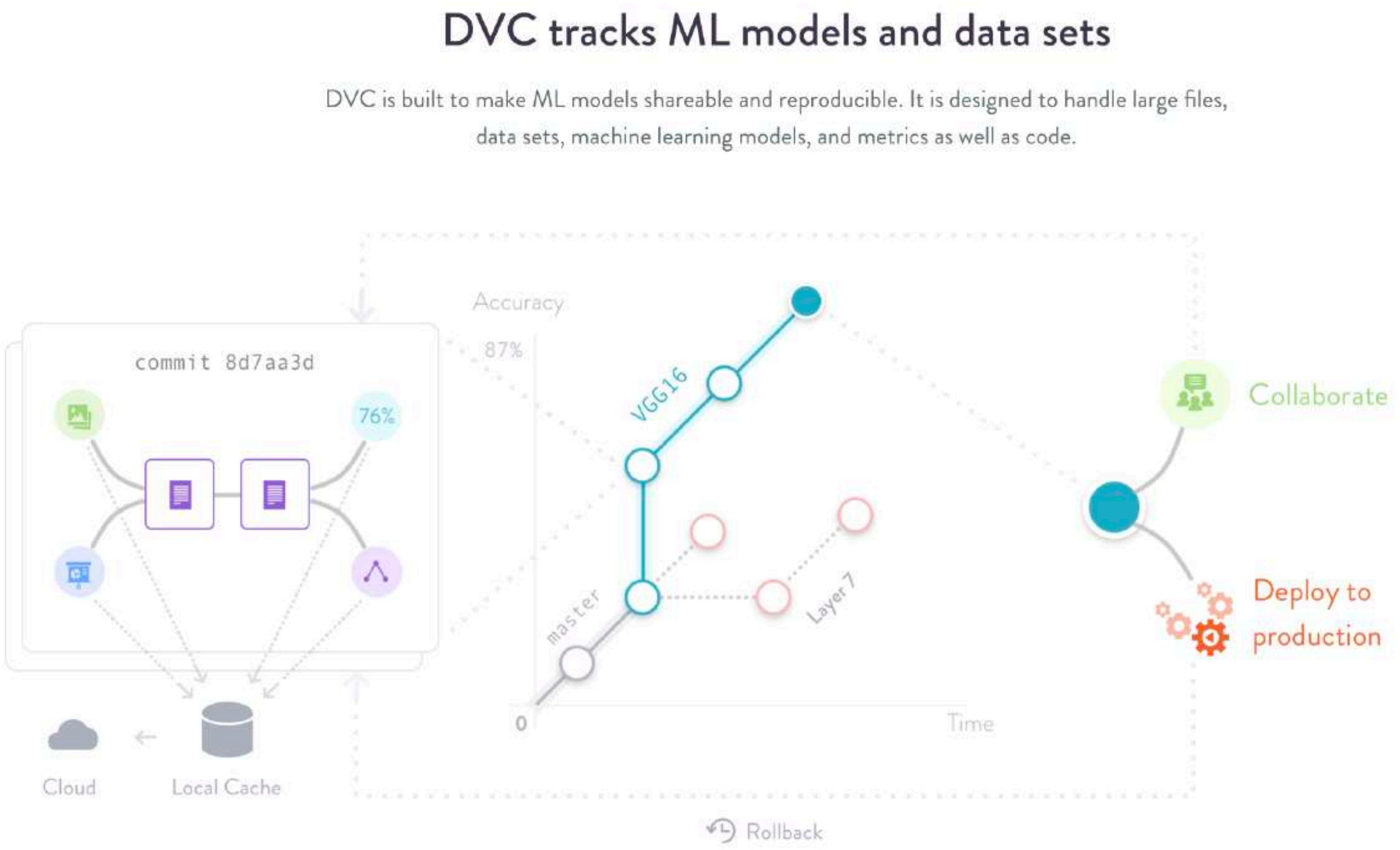
[1] https://www.wandb.com/
[2] https://www.comet.ml/
[3] https://neptune.ai/
[4] https://tensorboard.dev/
[5] https://clear.ml/

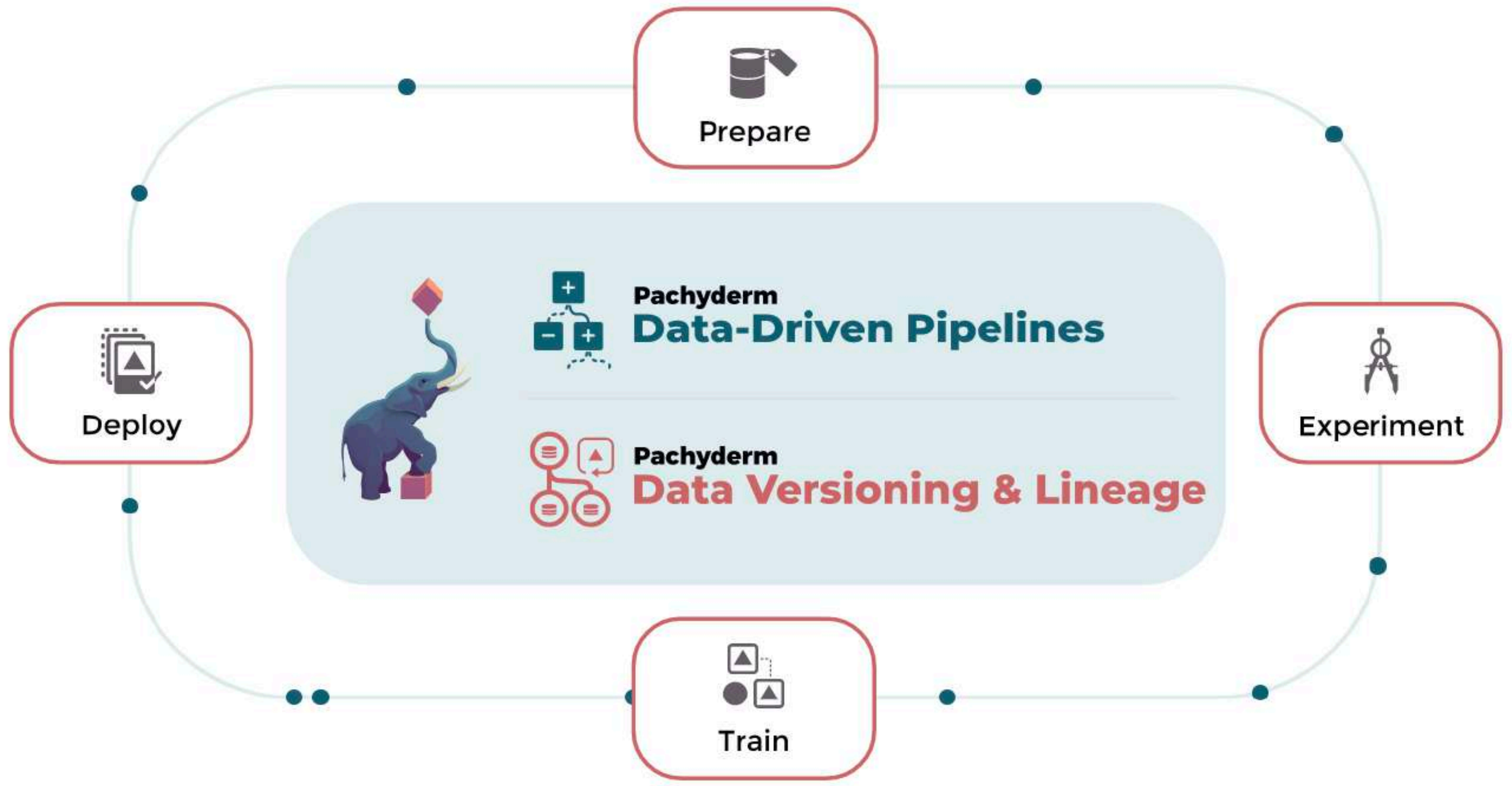
Data versioning

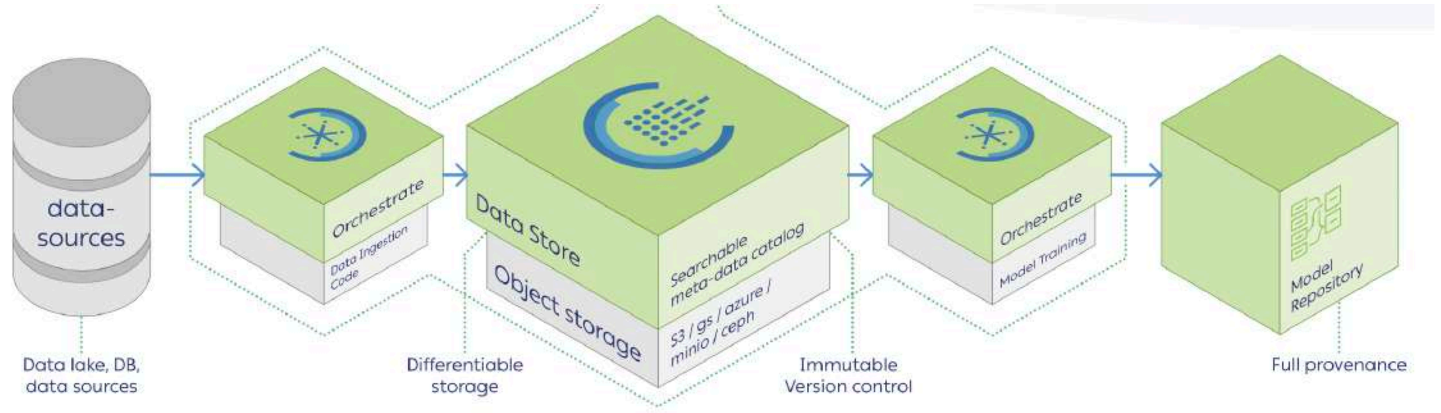
- Code is not the only component in your system
- Data is a crucial dependency, especially in complicated pipelines
- Tracking changes in it is equally important
- Pinning each experiment to its data enhances reproducibility

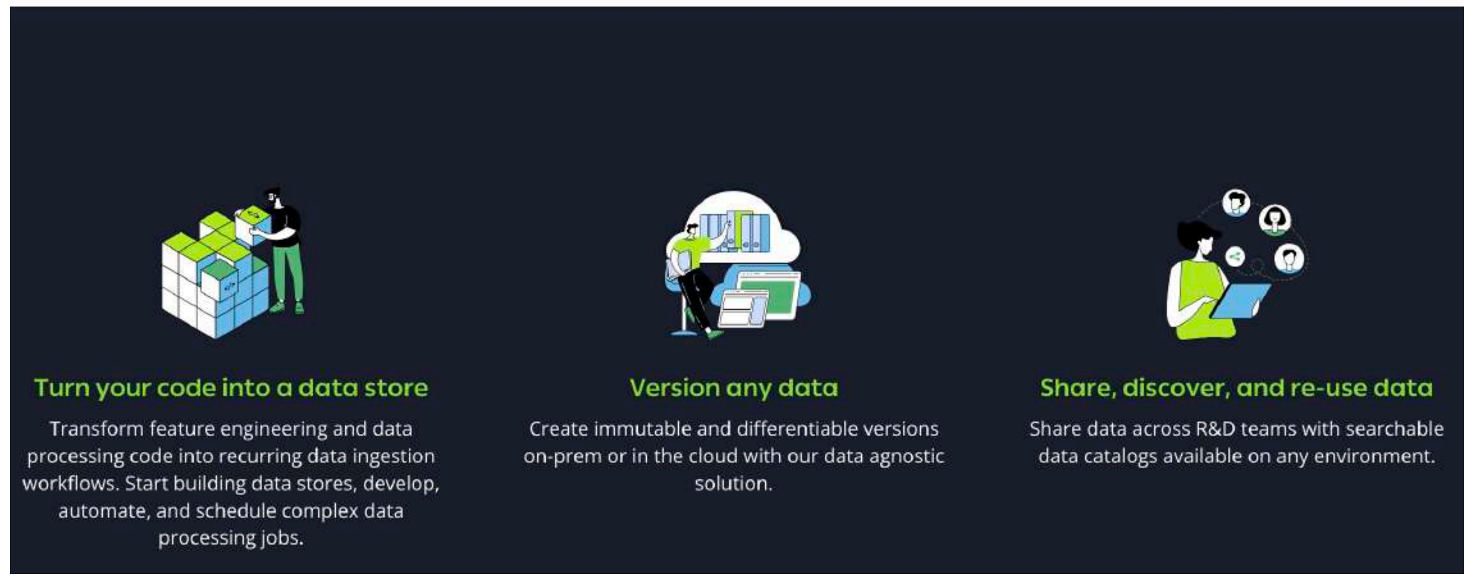
Solutions

- Several existing projects allow to integrate artifact versioning into pipelines
- Support external storage, matching with commits, metric comparison
- Possible to rerun specific parts of the pipeline on data/config change









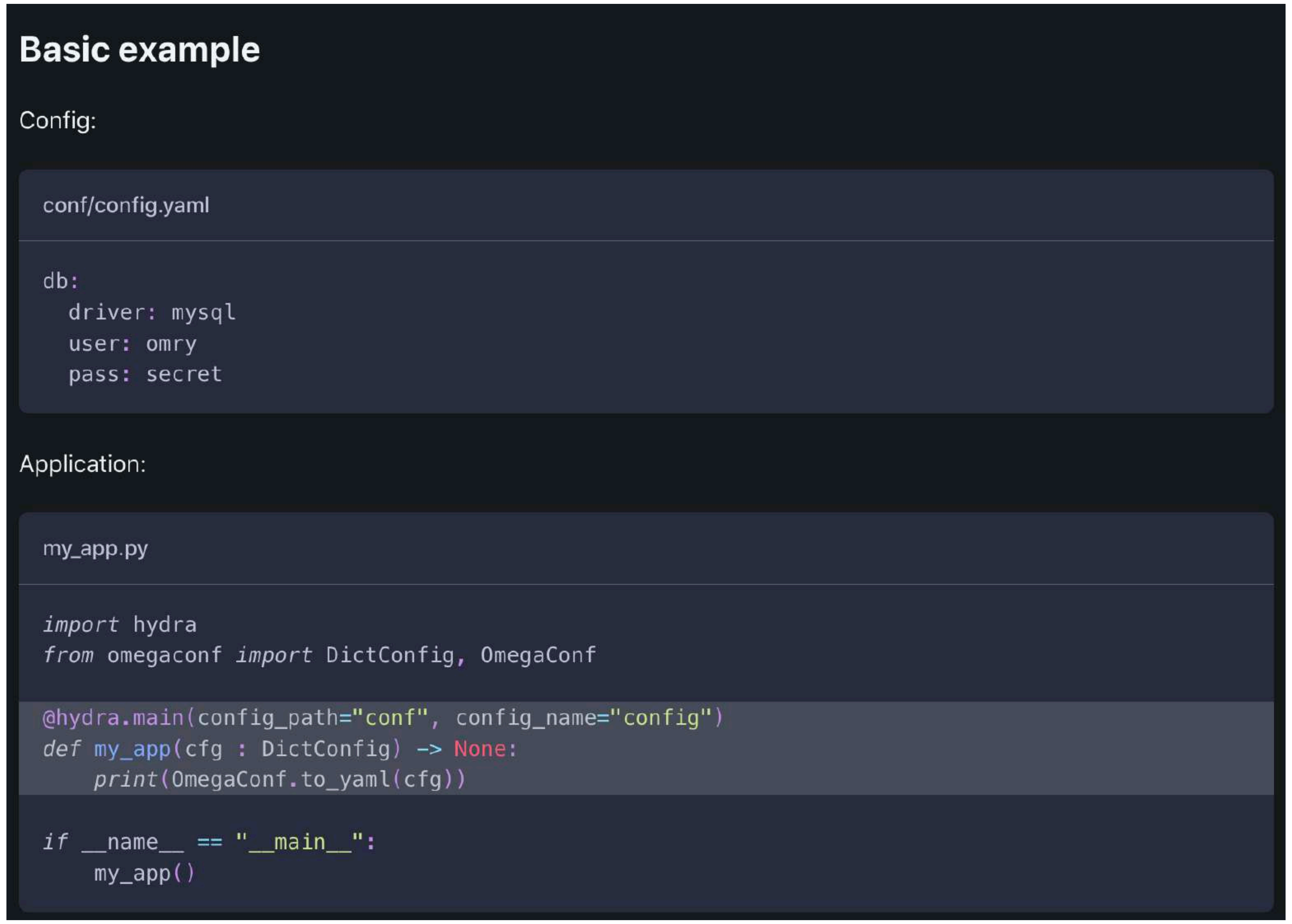
https://dvc.org/ https://www.pachyderm.com/ https://clear.ml/

Configuration

- As your project grows, the number of “moving parts” increases
    - Infrastructure: API endpoints, data URLs, etc.
    - Model hyperparameters and components
- Changing them manually across the entire repo is not sustainable
- `argparse`/`click`-based solutions are hard to write and properly version
- Hardcoding values in dedicated Python files is not flexible enough

Hydra

- One of the most popular solutions for handling configuration
- Uses YAML configs, allows overriding values from the command line
- Simple type checking via Structured Configs
- Grouped configs offer easy switching between groups of presets



Basic example

Config:

conf/config.yaml

```yaml
db:
  driver: mysql
  user: omry
  pass: secret
```

Application:

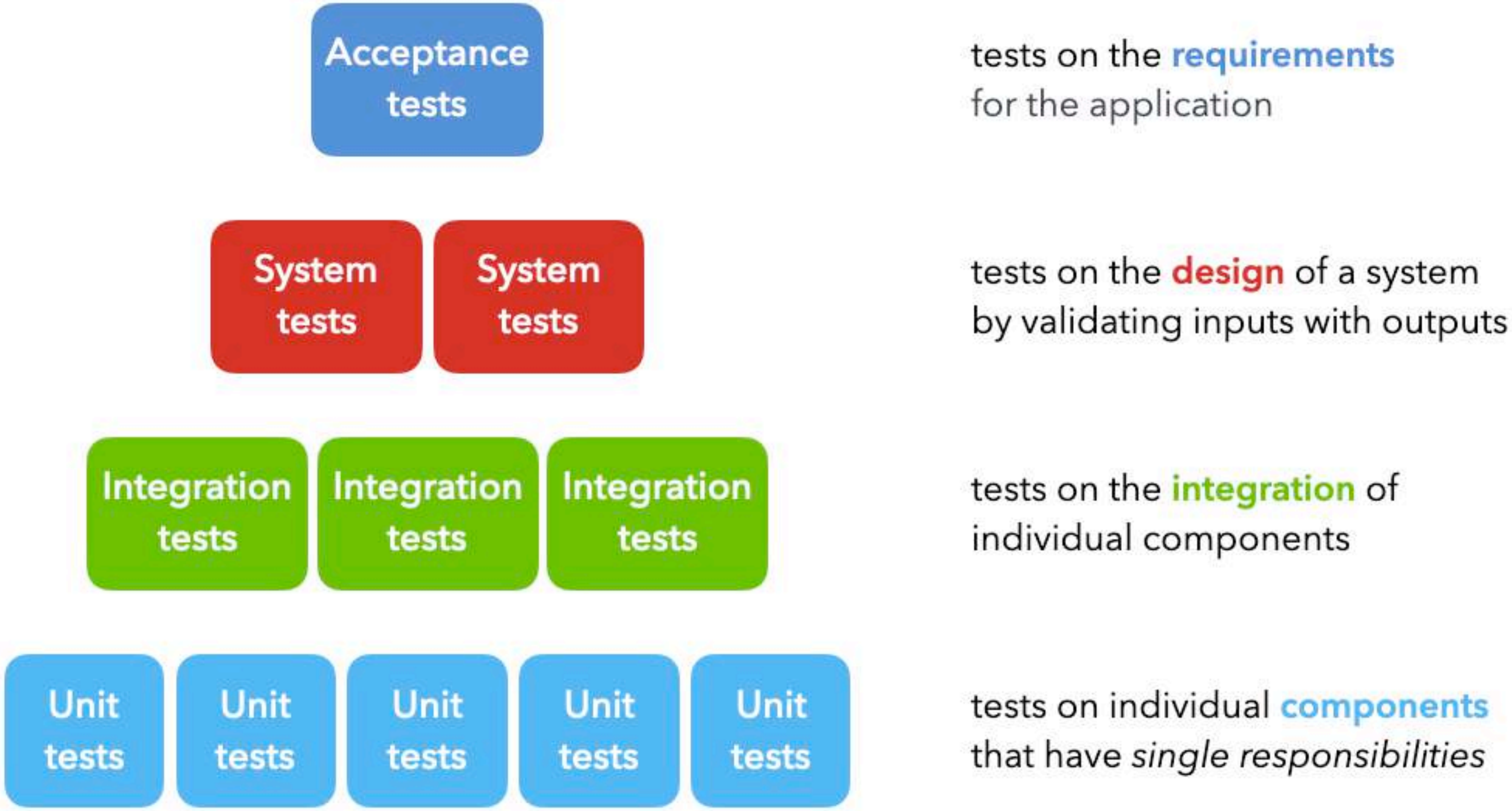
my_app.py

```python
import hydra
from omegaconf import DictConfig, OmegaConf

@hydra.main(config_path="conf", config_name="config")
def my_app(cfg : DictConfig) -> None:
    print(OmegaConf.to_yaml(cfg))

if __name__ == "__main__":
    my_app()
```

Testing

- In general, testing refers to verifying the intended code properties:
  - Not only correctness, but also performance, handling inputs, etc.
- Why should we test our code?
  - It helps avoid the bugs (both now and when refactoring)
  - But it **does not** prevent them! Treat tests like classifiers applied to your code
  - It improves the overall code quality by decoupling
  - Essentially, you get self-documented code for free

Types of software tests



https://madewithml.com/courses/mlops/testing/

Types of software tests

- There are many kinds and typologies, e.g.:
    1. **Unit tests** verify the correctness of a single component
    2. **Integration tests** ensure that modules work together
    3. **End-to-end tests** verify that the entire application is correct
    4. **Stress/load/performance** tests check the speed of code under load
- We'll focus on 1 and 2: they are the easiest to write and cover most cases

https://www.atlassian.com/continuous-delivery/software-testing/types-of-software-testing
https://hackr.io/blog/types-of-software-testing

How to test Python code

- Python built-in: unittest
  - Quite simple, ready to use
  - Cons: has its own syntax, not that flexible

```python
import unittest

class TestStringMethods(unittest.TestCase):

    def test_upper(self):
        self.assertEqual('foo'.upper(), 'FOO')

    def test_isupper(self):
        self.assertTrue('FOO'.isupper())
        self.assertFalse('Foo'.isupper())

    def test_split(self):
        s = 'hello world'
        self.assertEqual(s.split(), ['hello', 'world'])
        # check that s.split fails when the separator is not a string
        with self.assertRaises(TypeError):
            s.split(2)

if __name__ == '__main__':
    unittest.main()
```

```
...
----------------------------------------------------------------------
Ran 3 tests in 0.000s

OK
```

How to test Python code

- Python built-in: unittest
  - Quite simple, ready to use
  - Cons: has its own syntax, not that flexible
- Better: pytest
  - Flexible, works with assert statements, has plenty of integrations via plugins

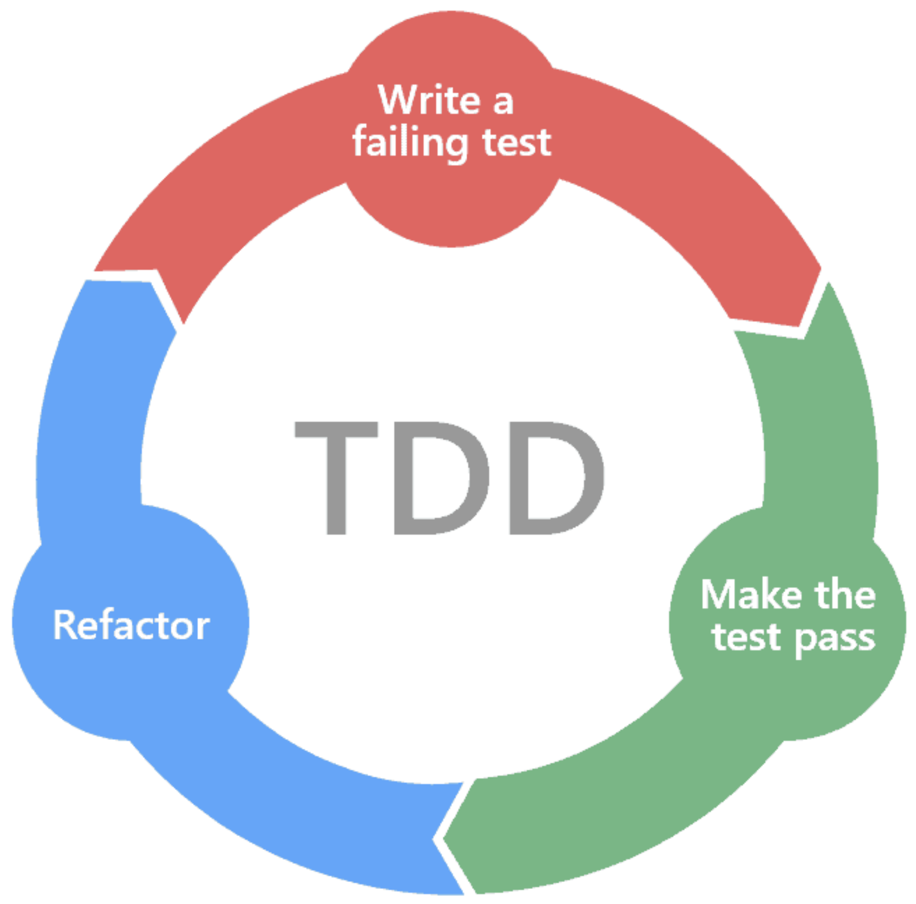
```
...
----------------------------------------------------------------------
Ran 3 tests in 0.000s

OK
```

```python
# content of test_sample.py
def func(x):
    return x + 1


def test_answer():
    assert func(3) == 5
```

```
$ pytest
=========================== test session starts ============================
platform linux -- Python 3.x.y, pytest-6.x.y, py-1.x.y, pluggy-1.x.y
cachedir: $PYTHON_PREFIX/.pytest_cache
rootdir: $REGENDOC_TMPDIR
collected 1 item

test_sample.py F                                                     [100%]

================================= FAILURES =================================
_______________________________ test_answer ________________________________

    def test_answer():
>       assert func(3) == 5
E       assert 4 == 5
E        +  where 4 = func(3)

test_sample.py:6: AssertionError
========================= short test summary info ==========================
FAILED test_sample.py::test_answer - assert 4 == 5
============================ 1 failed in 0.12s =============================
```

Test-driven development in ML context

- We can start from business requirements
- **Keep tests a natural part of your workflow!**
  This means getting a convenient setup
  both locally and in CI
- Leverage TDD for your ML code as well
- Test the expected changes in behavior of your model



Property-based testing

- How do we generate test cases?
    - Coming up with our own inputs is not exhaustive
    - Basically, we only test that <u>the code works for given inputs</u>
    - Furthermore, our <u>requirements become unclear</u>
- Property-based testing aims to solve this problem
    - Instead of specifying exact inputs, we tell what they should be
    - The framework tests the code on many inputs and tries to simplify failing cases

Hypothesis

- A Python framework for property-based-testing

- Integrates with pytest

- Has strategies for generating NumPy arrays (which generalizes to PyTorch tensors)

```python
from hypothesis import given, strategies as st


@given(st.integers(), st.integers())
def test_ints_are_commutative(x, y):
    assert x + y == y + x


@given(x=st.integers(), y=st.integers())
def test_ints_cancel(x, y):
    assert (x + y) - y == x


@given(st.lists(st.integers()))
def test_reversing_twice_gives_same_list(xs):
    # This will generate lists of arbitrary length (usually between 0 and
    # 100 elements) whose elements are integers.
    ys = list(xs)
    ys.reverse()
    ys.reverse()
    assert xs == ys


@given(st.tuples(st.booleans(), st.text()))
def test_look_tuples_work_too(t):
    # A tuple is generated as the one you provided, with the corresponding
    # types in those positions.
    assert len(t) == 2
    assert isinstance(t[0], bool)
    assert isinstance(t[1], str)
```

```python
>>> import numpy as np
>>> from hypothesis.strategies import floats
>>> arrays(np.float, 3, elements=floats(0, 1)).example()
array([ 0.88974794,  0.77387938,  0.1977879 ])
```