Structuring Machine Learning Projects

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Agenda

- Machine learning: From a software engineer’s keystrokes
- Why care about the structure?
- A **structured** approach to **structuring**
  - A polished directory structure
  - Workspace setup
  - Building mental models of the project’s flow
  - Experimentation
  - ....
- Taking the next steps
- Guiding lights

Life-cycle of a machine learning project

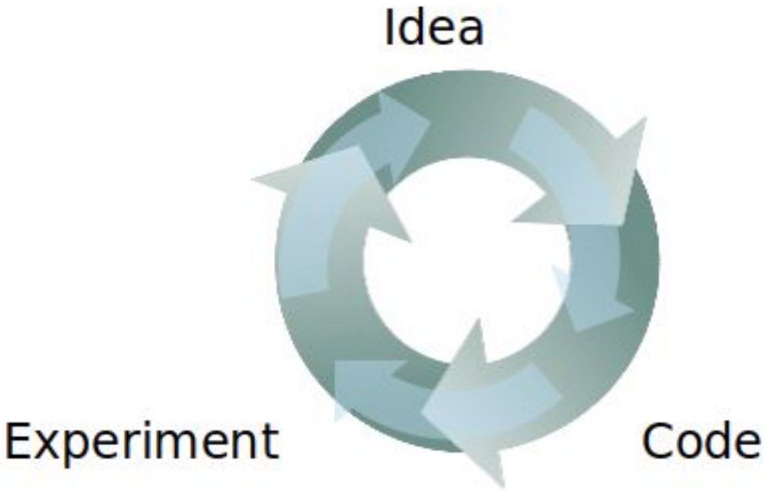
- Problem understanding
- Data collection, wrangling and so on
- Understanding of the data
- Beginning the modeling process
- Evaluate, tune, repeat
- Model deployment, monitoring and so on...

Note that the above steps are very summarized

Structuring machine learning projects: The need

Applied machine (and deep) learning is iterative

- Lots of experimentations make it hard to keep track
- Hyperparameter tuning
- Dataset reconstructions
- KPI: Time-Cost tradeoff



Source

Reproducibility crisis

- **Stochasticity** in machine learning models (neural nets specifically)
- Code breakdown due to dependency mismatches
- Difference in machine configurations

Versioning data and codebase

- Training data might change over time (less frequent)

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Versioning data and codebase

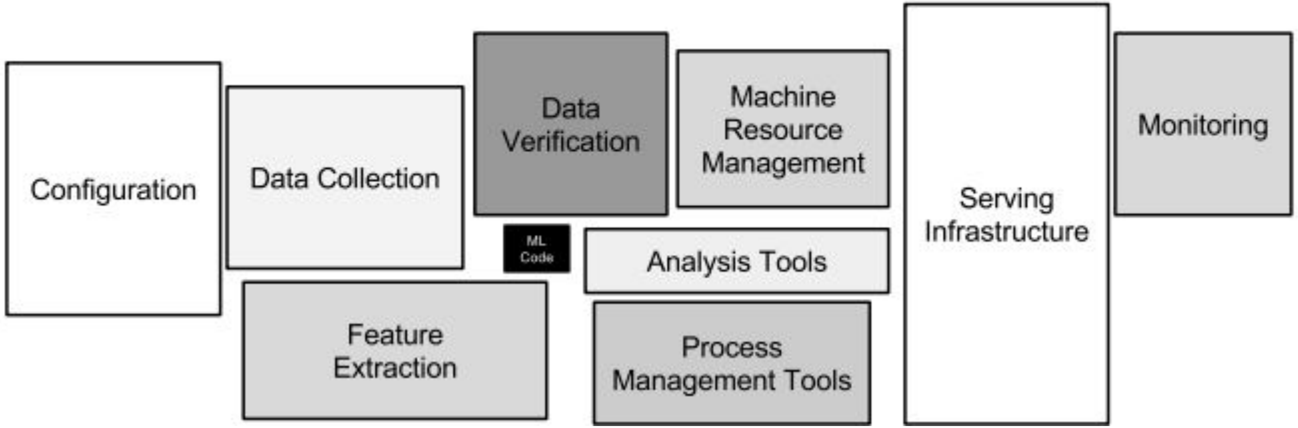
- Training data might change over time (less frequent)
- Changes in project's codebase are far more frequent

Regularity in checkpointing

Decrease in validation loss was steady during the training, but what if that model is lost?

A directory structure

- A full-fledged ML project is **not just about models**



[Source]

A high-interest technical debt

- Lots of ideas, lots of experiments - gives birth to **technical debt**
- Not everyone in the team understands everything
- Lack of *documentation* as it is considered *not-so-cool*

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This hurts the overall development of the project!

Quick summary

- Applied machine learning is an iterative process
- Reproducibility crisis
- Versioning data and codebase
- Regularity in checkpointing
- Directory structures
- Technical debt

Structuring Machine Learning projects: A definitive approach

Starting with a polished directory structure

- Data (along with scripts to *download it* and *preprocess it*)
- Experimentations
- Web backend
- Utility scripts
- Model building and model training scripts

A reference directory structure

```
apparel_classifier/              # Package that can be deployed as a self-contained prediction system
  __init__.py

  apparel_predictor.py      # Takes a raw image and obtains a prediction

  datasets/                     # Code for loading datasets
      __init__.py
      dataset.py                # Base class for datasets - logic for downloading data (if not available)
      fmnist_dataset.py
      fmnist_essentials.json
      dataset_sequence.py

  models/                       # Code for instantiating models, including data preprocessing and loss functions
      __init__.py
      base.py                   # Base class for models
      image_model.py

  networks/          # Code for building neural networks (i.e., 'dumb' input->output mappings) used by models
      __init__.py
      mlp.py

  tests/
      support/                          # Raw data used by tests
      test_apparel_predictor.py       # Test model on a few key examples

  weights/                              # Weights for production model
      Image_Model_FMNIST_Dataset_weights.h5

  util.py

training/                        # Code for running training experiments and selecting the best model.
    run_experiment.py            # Parse experiment config and launch training.
    util.py                      # Logic for training a model with a given config
```

Workspace setup

- Use of environment management tools - **pipenv**, **virtualenv** etc
- Incorporating containers - **Docker**, **Kubernetes** etc
- Use of unified machine learning platforms like FloydHub

Keeping track of the experiments

Machine learning experiments have a lot of components:

- Loss/Accuracy metrics
- Model parameters
- CPU, GPU and disk usage

And so on ...

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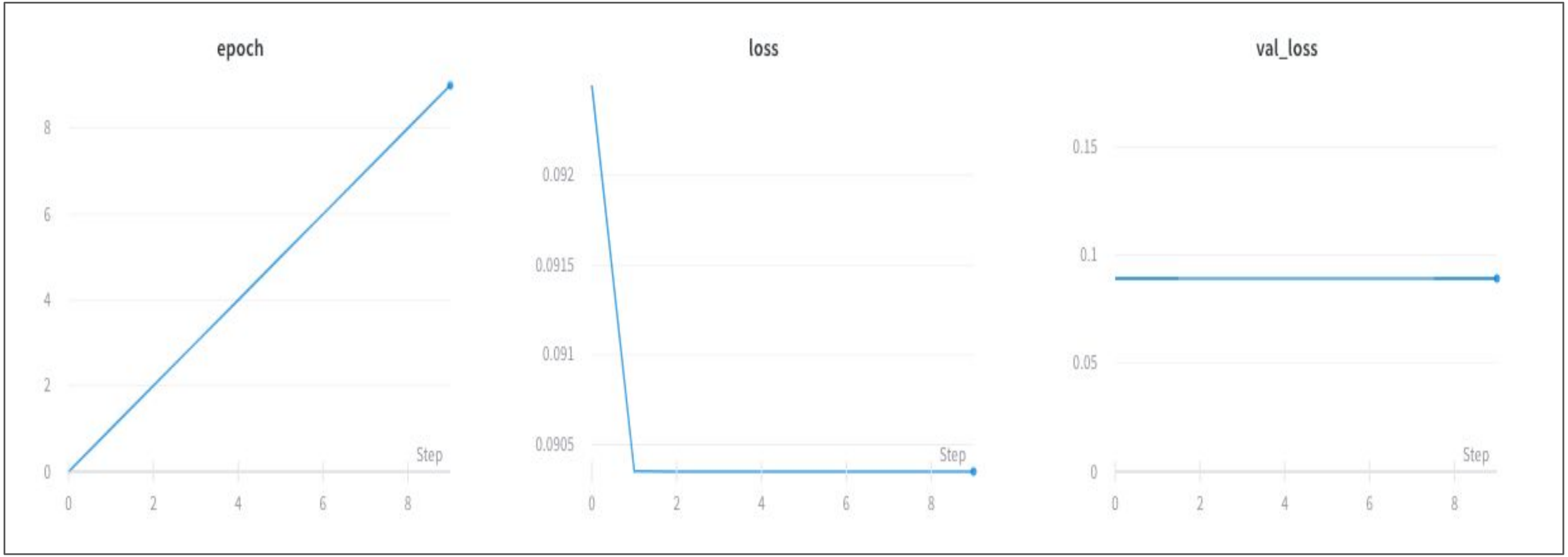
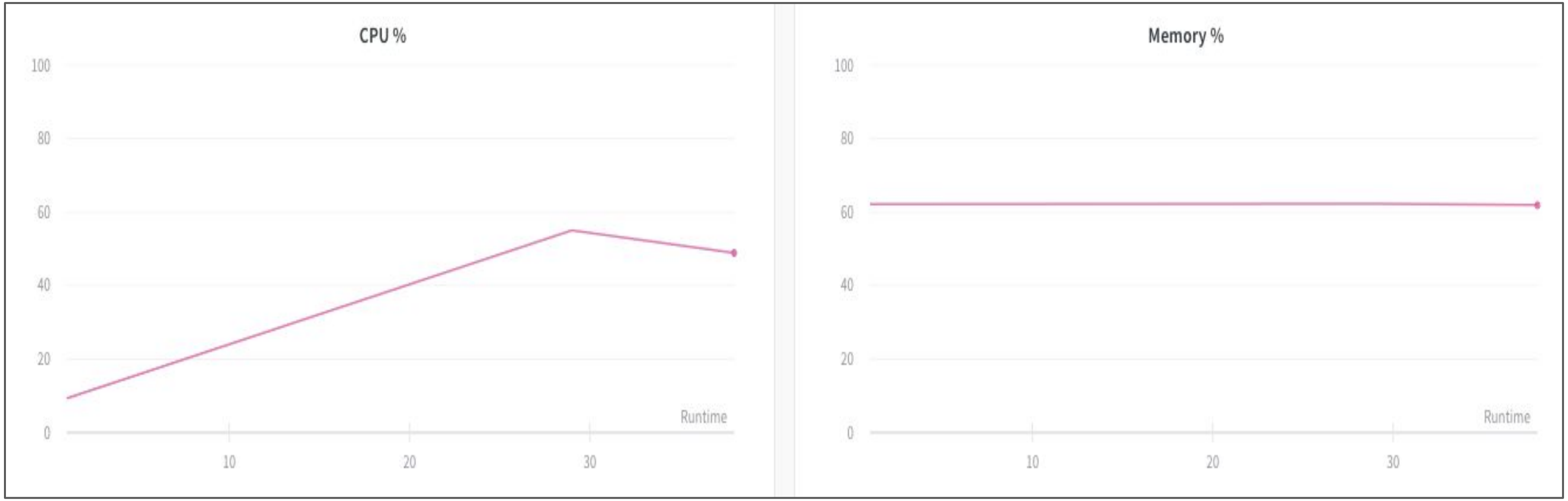
Use **Weights and Biases** to keep track of these for you on the **cloud**!


epoch
loss
val_loss
Step
0
2
4
6
8
0.092
0.0915
0.091
0.0905
0.15
0.1
0.05


CPU %
100
80
60
40
20
0
Runtime
10
20
30
Memory %
100
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0
Runtime
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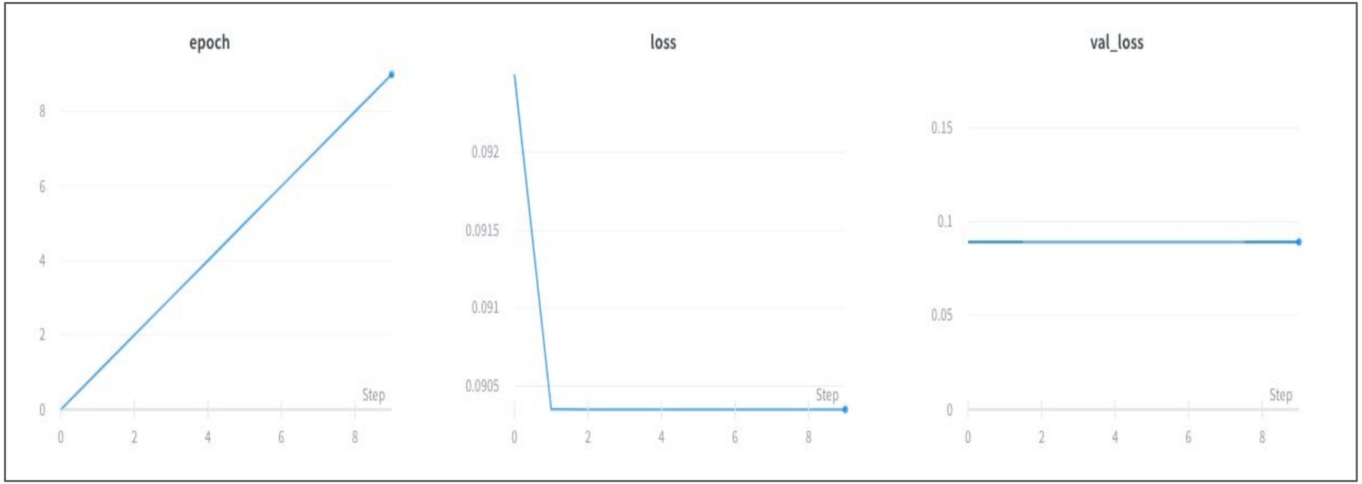
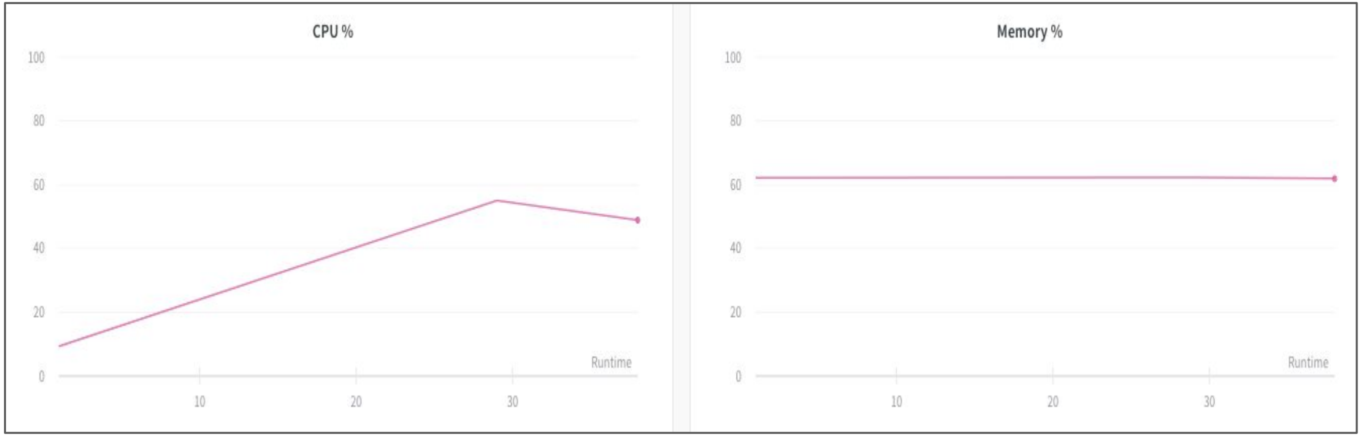
20
30





And many things more!

Building a mental image of the execution flow

- There will be a lot of inter-connected blocks in a project
  - A block can have several sub-blocks too

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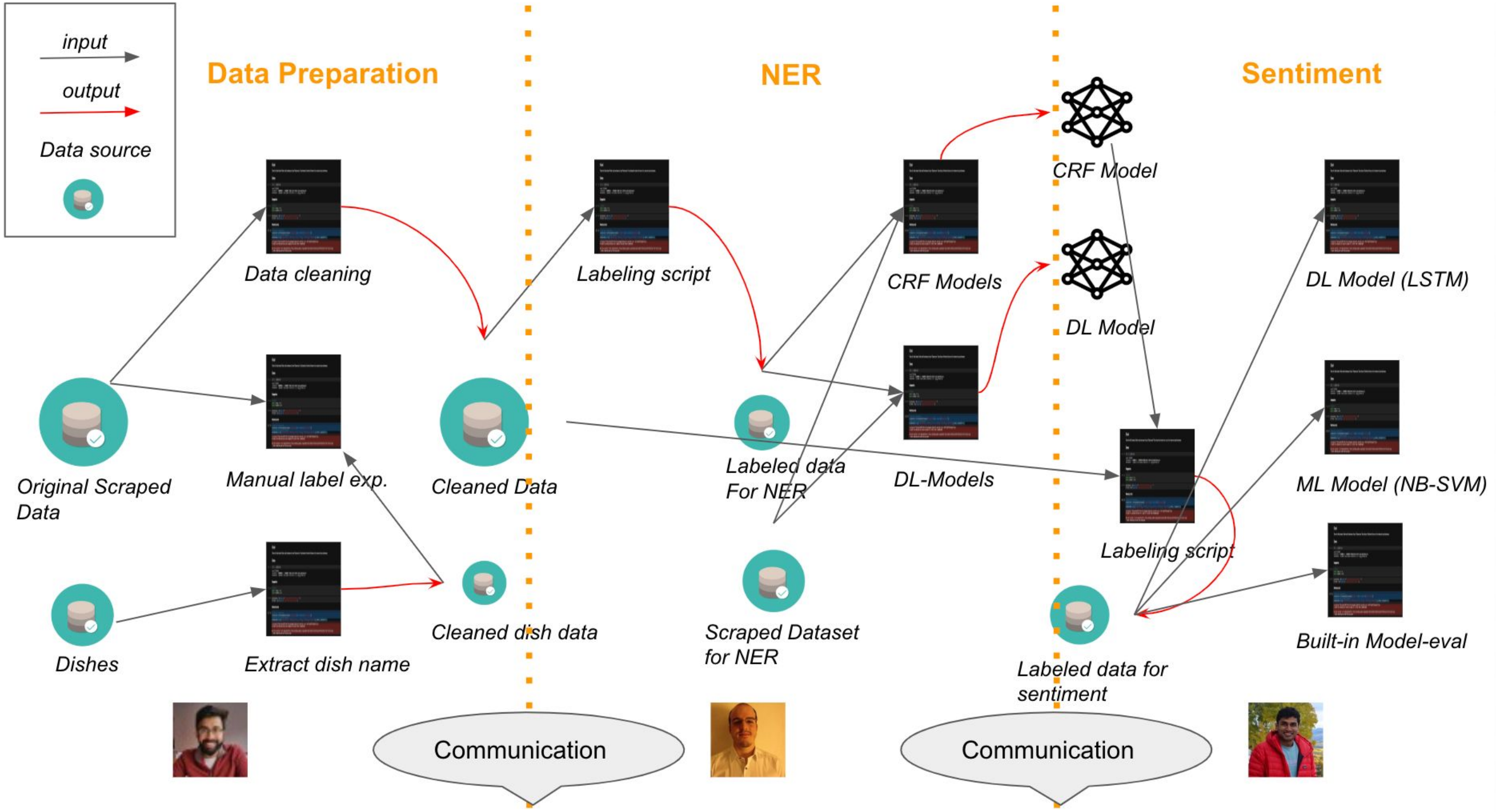
Hence a mental model to keep track of these lego blocks always helps!

A specimen of a mental model



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Version controlling data and codebase *separately*

Here are some situations:

- Need to replace the older images with newer ones
- Need to add new images to an already existing training set
- Decision to incorporate active learning to select interesting test data points to manually label them and add to the existing training set

Version controlling data and codebase *separately*

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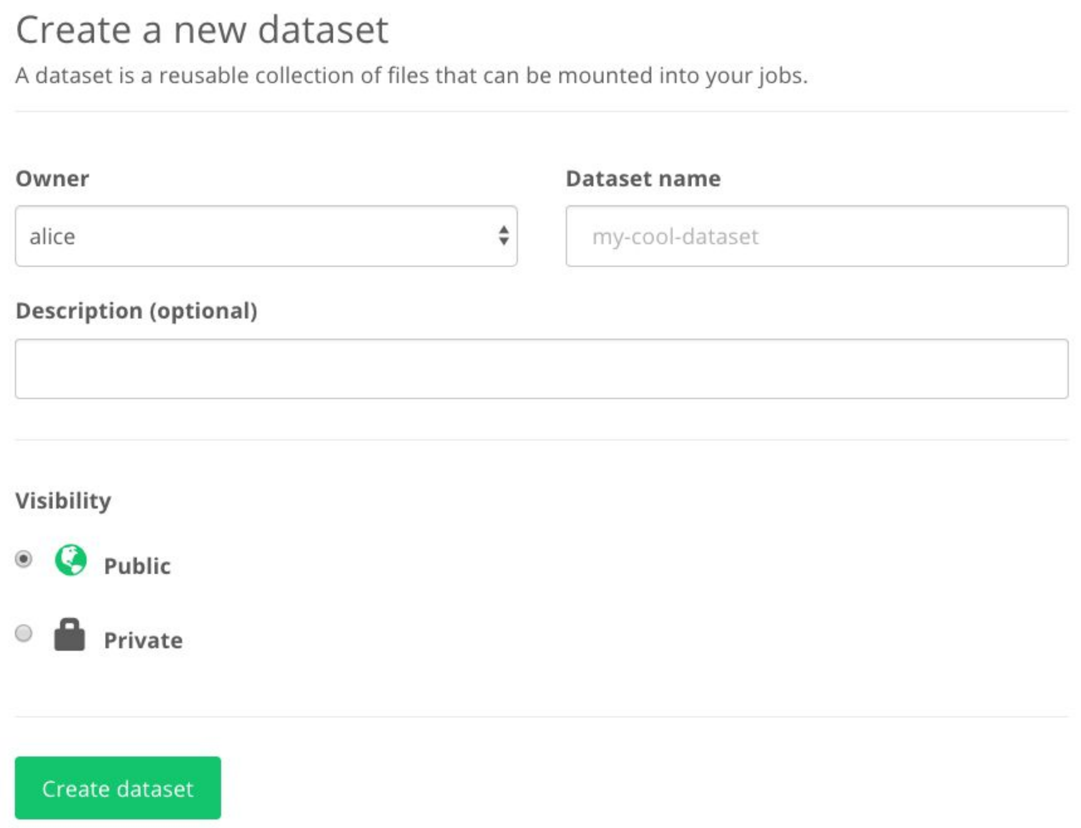
Version control of codebase remains traditional!

FloydHub datasets



FloydHub datasets are a good way to version control your data!

Quick summary

- Maintaining a healthy directory structure
- Setting up the workspace
- Keeping track of your experiments
- Building a mental model of the project flow
- Version control of data and codebase

What did we *not* cover?

- Test cases for machine learning projects
- Model deployment

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- Test cases for machine learning projects
- Model deployment

Maybe next time :)

References

- [How to plan and execute your ML and DL projects]
- [Troubleshooting Deep Neural Networks]
- [Production Machine Learning Systems]

See you next time

Find me here:
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Thank you very much :)

Experts

pyimagesearch