Structuring Machine Learning Projects

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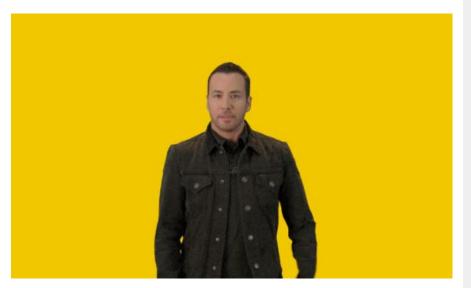


Agenda

- Machine learning: The life-cycle
- 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
 - O
- Taking the next steps
- Guiding lights

Life-cycle of a machine learning project

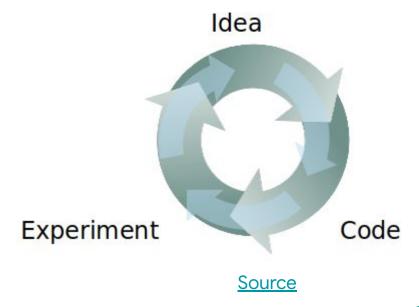
- Problem understanding
- Data collection, wrangling and so on
- Understanding of the data
- Beginning the modeling process
- Evaluate, tune, repeat
- Model deployment, monitoring and so on...



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



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)

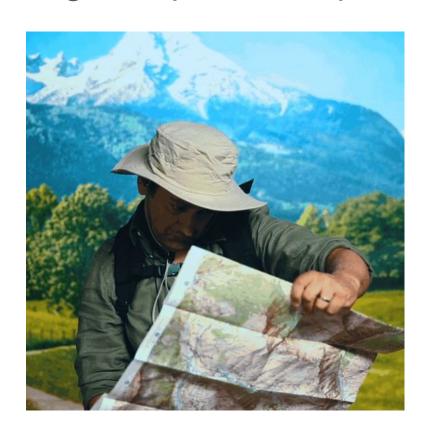
Versioning data and codebase

• Training data might change over time (less frequent) —— Pain point!

Versioning data and codebase

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

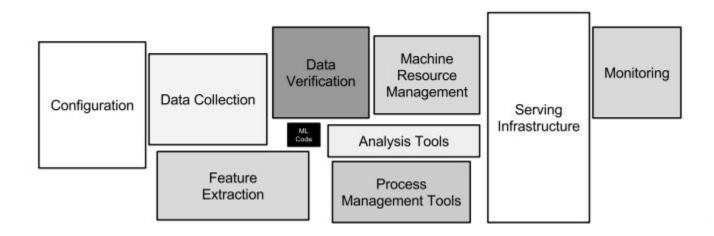
Regularity in checkpointing



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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Machine Learning:
The High-Interest Credit Card of Technical Debt

D. Sculley, Gary Holt, Daniel Golovin, Eugene Davydov,
Todd Phillips, Dietmar Ebner, Vinay Chaudhary, Michael Young
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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/
  apparel predictor.py
  datasets/
     dataset.py
     fmnist dataset.py
     fmnist_essentials.json
     dataset sequence.py
  models/
     base.py
      image_model.py
  networks/
      __init__.py
     mlp.py
  tests/
      support/
      test_apparel_predictor.py
  weights/
      Image Model FMNIST Dataset weights.h5
  util.py
training/
    run_experiment.py
    util.py
```

Workspace setup

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

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 ...

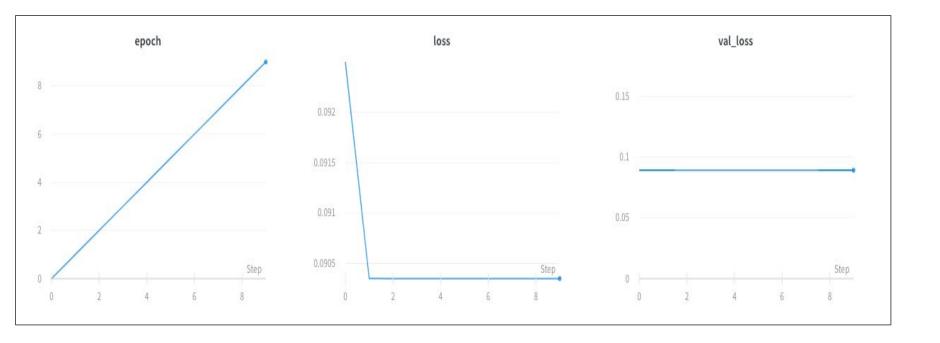
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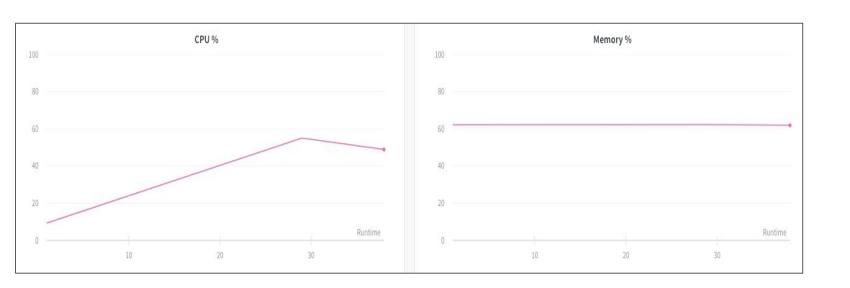
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And so on ...

Use <u>Weights and Biases</u> to automatically keep track of these for you on the **cloud**!





• Name (28	State	Notes	User	Tags	Created	Runtime	Sweep	epochs	layers	accuracy	epoch	loss	val_accu	val_loss ▼
● a	finished	Add notes	saya		1mo ago	35s	6v8m5w0s	5	32	0.8795	4	0.3328	0.869	0.3756
• • d	finished	Add notes	saya		1mo ago	9m 36s	÷	5	128	0.8918	4	0.2932	0.8693	0.3692
• • 1	finished	Add notes	saya		1mo ago	42s	6v8m5w0s	5	96	0.8895	4	0.3023	0.8691	0.3664
• • z	finished	Add notes	saya		1mo ago	34s	6v8m5w0s	5	128	0.8906	4	0.2958	0.8729	0.3563
• • 1	finished	Add notes	saya		1mo ago	39s	6v8m5w0s	5	64	0.8869	4	0.3093	0.8747	0.35
• • p	finished	Add notes	saya		1mo ago	42s	6v8m5w0s	5	256	0.895	4	0.2834	0.8696	0.3488

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Try it out here:

http://bit.ly/w_and_b

Building a mental image of the execution flow

• There will be a lot of inter-connected blocks in a project

Building a mental image of the execution flow

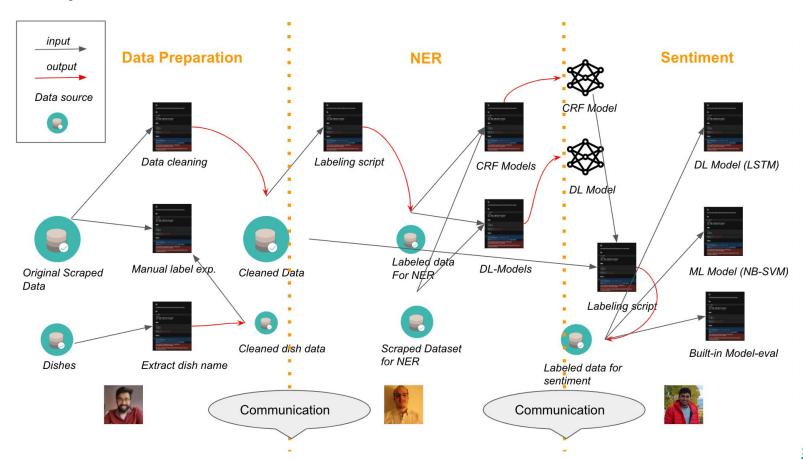
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 - A block can have several sub-blocks too

Building a mental image of the execution flow

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 - A block can have several sub-blocks too

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

A specimen of a mental model



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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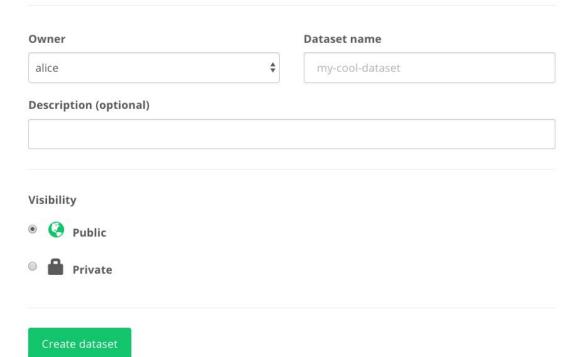
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Version control of codebase remains traditional!

FloydHub datasets

Create a new dataset

A dataset is a reusable collection of files that can be mounted into your jobs.



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:)

Slides available here: http://bit.ly/izmir-sayak

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: sayak.dev

Thank you very much:)



