Machine Learning Models and Dataset Versioning

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Outline

- Why ML is different from software eng?
- Problems on using git and git-LFS
- Other Open source Tools
- Why DVC is a good option
- Use case: Versioning Cats vs Dogs

What is ML?

- It provides an systems the ability to automatically learn and improve from experience without being explicitly programmed.

How ML is different?

Data science as different from software

as software was different from hardware.

- Nick Elprin

The rise of Software engineering required inventing new processes like version control, code review, agile, to help teams work effectively. The rise of AI & Machine Learning is now requiring new processes, ..

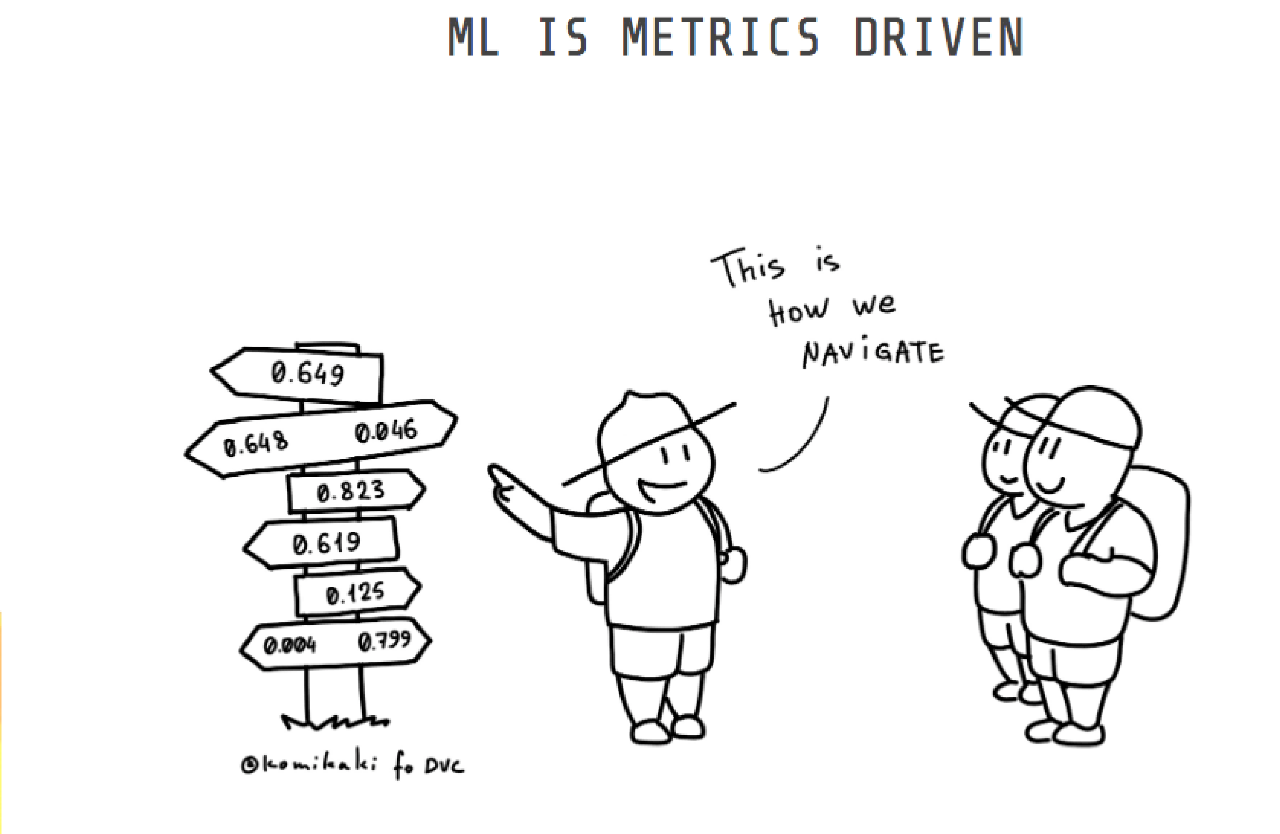
- Andrew Ng

Key Differences

- ML is metrics driven
- Enormous size of data and models
- Sharing of Models with teams
- Special purpose hardware
- Pipelines
- Difference in best practises

ML is metric driven

- We focus on improving metrics like accuracy, AUC, RUC.
- Aim to make SOTA models, rapidly experiment



Feature-driven Development

- While in software engineering, your team works by building new features.
- Use code-review and agile best practises.

Huge amount of Data dealed

- People work with lots of data for everything.
- Managing datasets are a problem
- Models – a byproduct :P

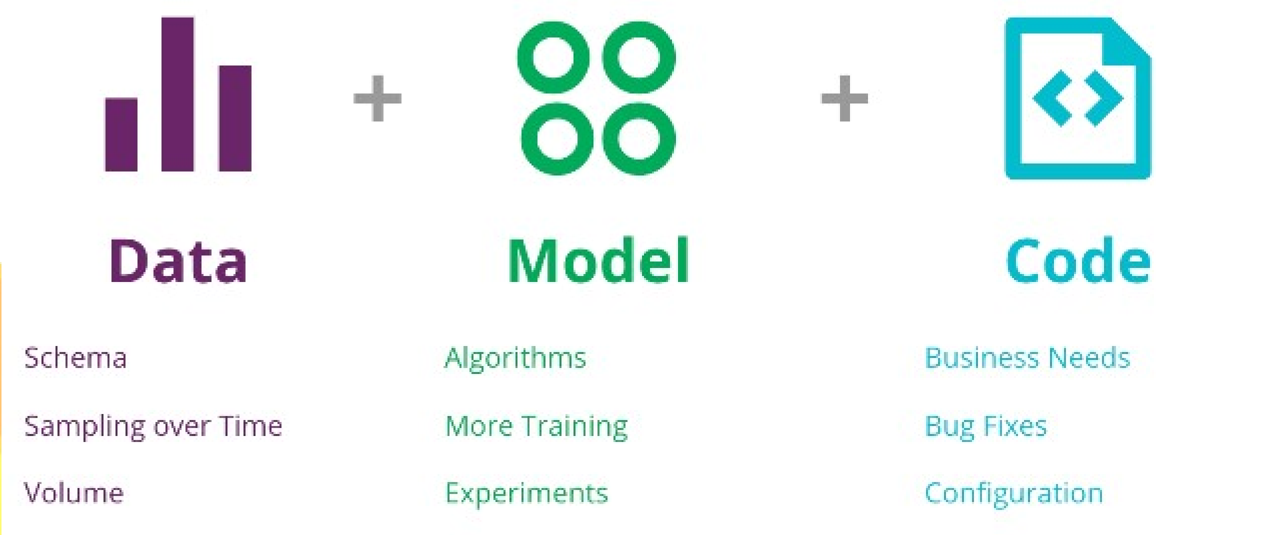
Huge amount of Data dealed

- People work with TB’s of data for everything.
- Managing datasets are a problem
- amount of data generated for a self-driving car (4 TB/day)

ML models need huge resources

- Most software product take a few minutes to run, which team can easily follow.

- Collabrative challenges faced when working with large teams and remotely.



Pipelines of different stages

- Defining process of steps at each duration like:

  - Input

  - Feature extraction

  - Classification

  - Final output

Special purpose hardwares

- Use of special TPUs and cloud Computing
- ML researchers have huge computation needs

Difference in best practises

- Use of Python PEP8 conventions are not always properly practised in jupyter notebooks.
- DataScience = software eng + science&maths

```
from fastai import *
```

Using git for large dataset

- Trying git for dataset of size of 1GB takes about 8-10 minutes to commit
- .gitignore – ignores Dataset versioning

Using git-LFS

“Git Large File Storage (LFS) replaces large files such as audio samples, videos, datasets, and graphics with text pointers inside Git, while storing the file contents on a remote server like GitHub.com or GitHub Enterprise.”

Using git-LFS

- There is a data limit of storing files of 2GB, which is a github limitation.
- Another issue is the ease of placing data files on a cloud storage system (AWS, GCP, etc) as is often required when to run cloud-based AI software.
- Not designed in mind with ML/data science

Other open source tools

- Data Version Control – Track experiments, data
- ML flow – Metric Tracking, Model Deployment
- Neptune.ml – Experiment Tracking, collabration
- Jovian – Share notebooks, easily reproducible
- hangar py – Version control for tensor data

Why DVC is a good option?

- It’s open source
- Has support for multiple cloud providers
- Support for:

  a) Pipelines

  b) Versioning ML models

  c) Versioning Datasets

  d) Tracking metrics
- “Made for Data scientist, by the Data scientist”

Using DVC with a problem

- We are going to work on a Classic Deep Learning problem like cats vs dogs:

initialising project

$ git clone https://github.com/iterative/example-versioning.git

$ cd example-versioning

1. Add the data to dvc

- We use 1000 labelled images of Cats and dogs at first

$ dvc add data → Add datafolder to dvc

$ python train.py

$ dvc add model.h5 → model is add to dvc

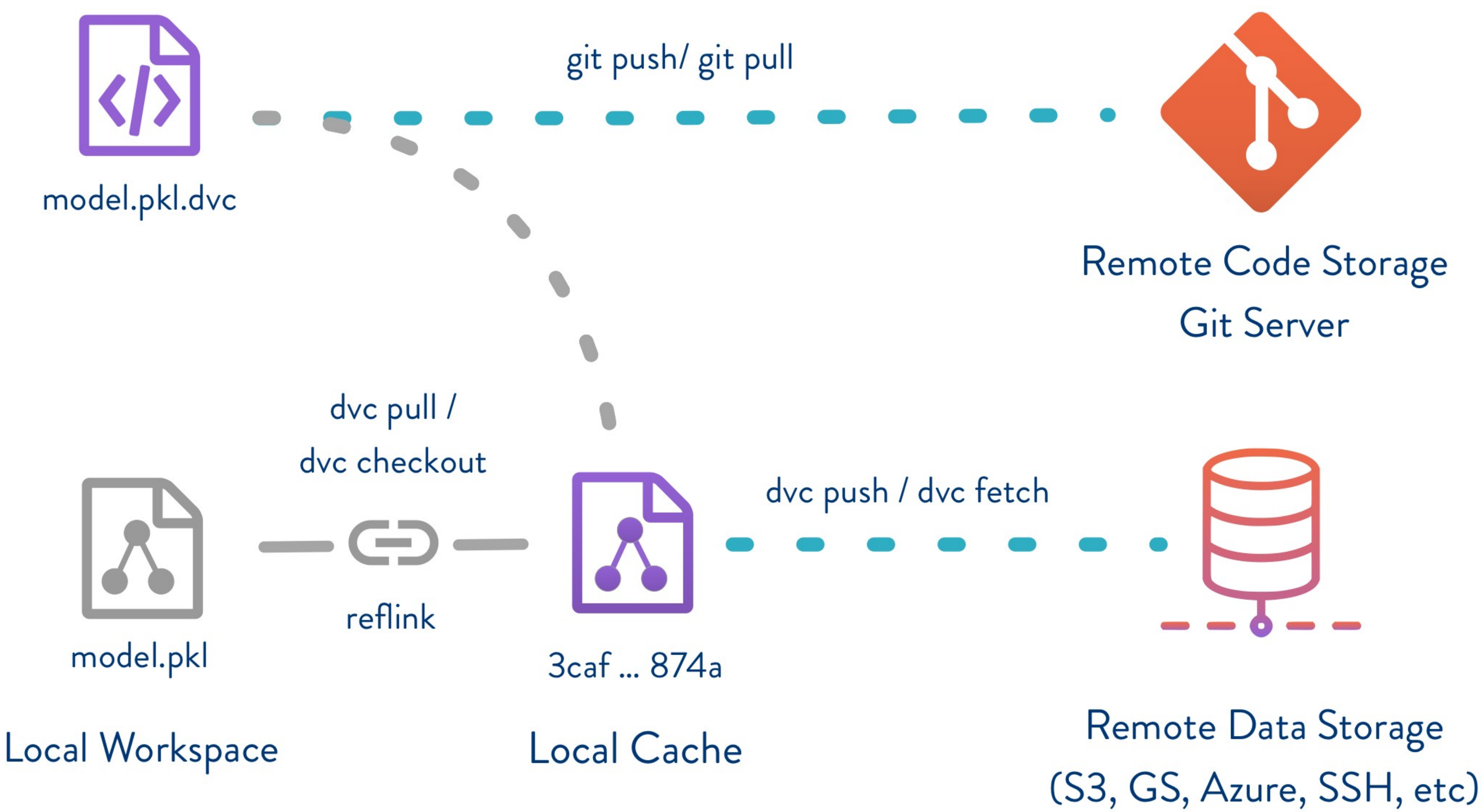
2. Track changes with git

```
$ git add .gitignore model.h5.dvc data.dvc metrics.json

$ git commit -m "First model, trained with 1000 images"

$ git tag -a "v1.0" -m "model v1.0, 1000 images"
```

3. Push changes to cloud

```
$ dvc push
$ dvc pull
```

- Data is pushed to remote server from local cache.
- DVC is storage agnostic and support s3, Azure, GCP, hdfs, ssh


git push/ git pull
model.pkl.dvc
Remote Code Storage
Git Server
dvc pull /
dvc checkout
dvc push / dvc fetch
reflink
model.pkl
3caf ... 874a
Local Workspace
Local Cache
Remote Data Storage
(S3, GS, Azure, SSH, etc)

4. Adding more labelled data

(downloading 1000 more images of labelled cat and dog images)

```
$ dvc add more_data
$ dvc remove model.h5.dvc
$ python train.py
$ dvc add model.h5
```

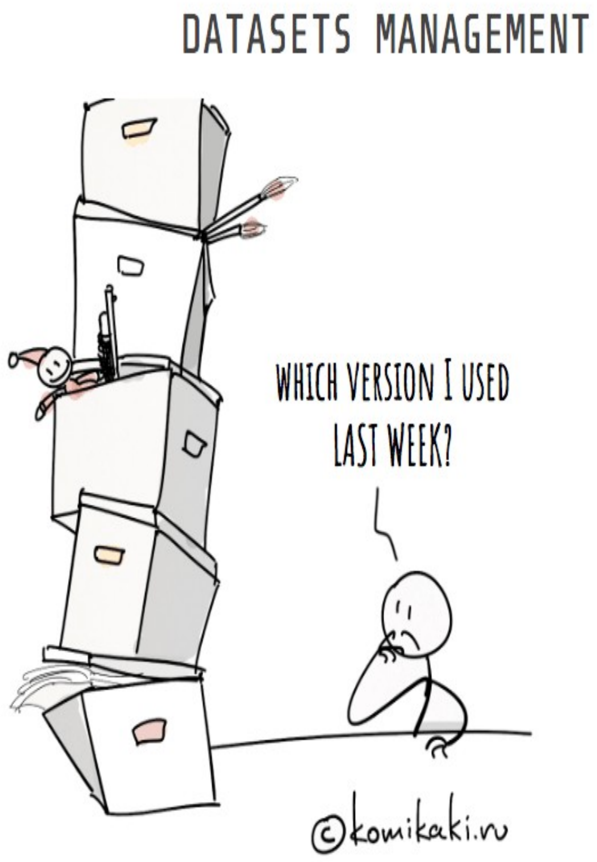
```
$ git add model.h5.dvc data.dvc metrics.json
$ git commit -m "Second model, trained with 2000 images"
$ git tag -a "v2.0" -m "model v2.0, 2000 images"
```

What is Dataset versioning?

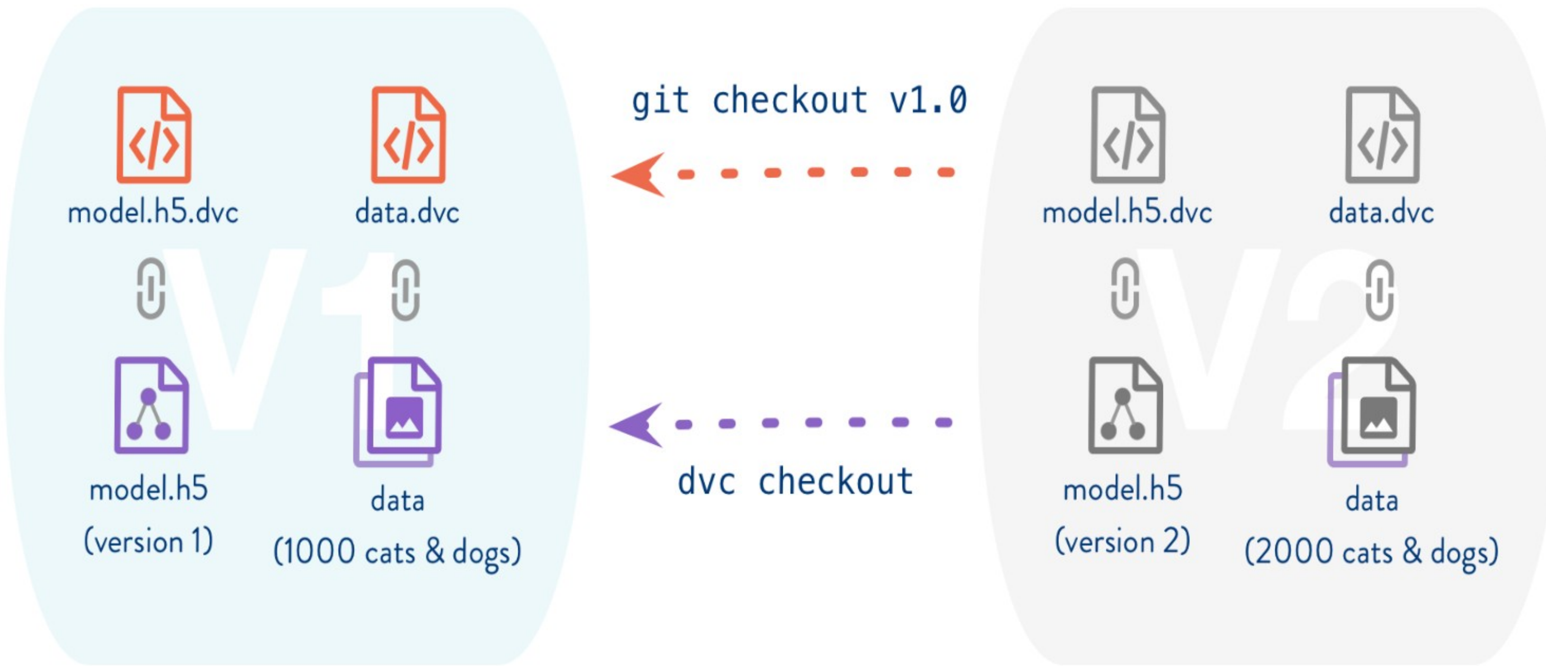
Tracking of data at each time

When working with TB's of data it's essential

Different splits for train/test/val



5. Switching between versions



$ git checkout v1.0

$ dvc checkout

6. Running experiments

$ dvc pull data_folder.dvc

$ dvc run <parameters>

DVC is internally building a dependency graph using dependencies, output and stores the result.

```
dvc run -f modelDvcfile \
        -d train.py -d data \
        -M metrics.json \
        -o model.h5 \
 -o bottleneck_features_train.npy \
        python train.py
```

d for dependency: specify an input file

o for output: specify an output file ignored by git and tracked by dvc

M for metric: specify an output file tracked by git

f for file: specify the name of the dvc file.

Model versioning

Models = Code + data + hyperparameters

- Everytime our hyperparameters are changed, we can have corresponding DVC files with store the changes
- You can even reproduce the old results

7. More Experiments

- I use VGG architecture for version1
- Then resnet for version2
- V2 made much more improv
  Bottle-necks
- Fine tune models

8. Iterating over experiments

- $ dvc repro train_v2.dvc
- $ dvc metrics show

ML Reproducibilty crisis

- Much of ML projects are not reproducible
- Managing the metrics and hyperparameters which changed this module is very important

Thank You