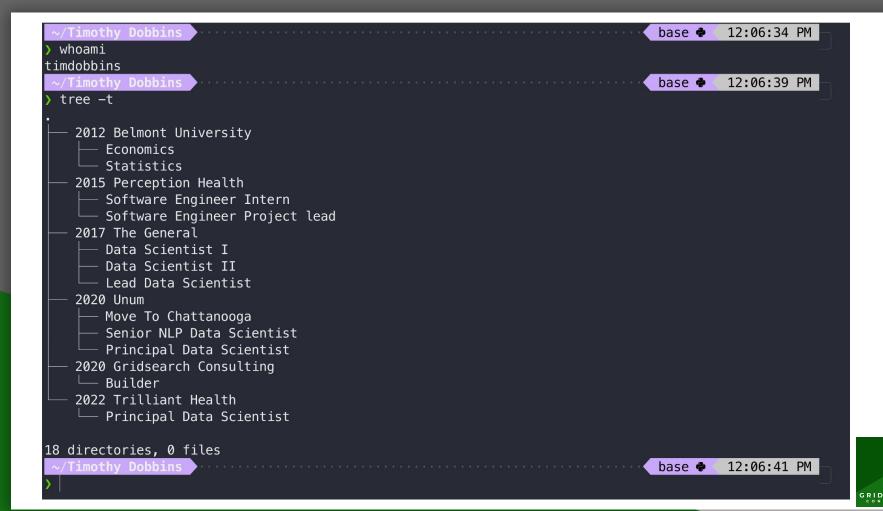
Reproducible Machine Learning

Why and how to accomplish reproducibility in ML pipelines





Who works with ML models that are in production?

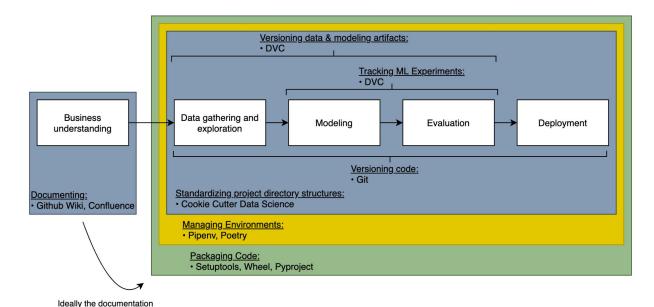


Who works with reproducible ML models?



An ML reproducibility framework*

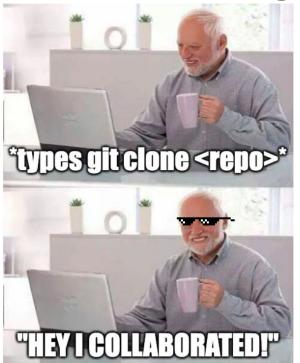
is linked to corresponding tickets (JIRA, Github)







Collaborating



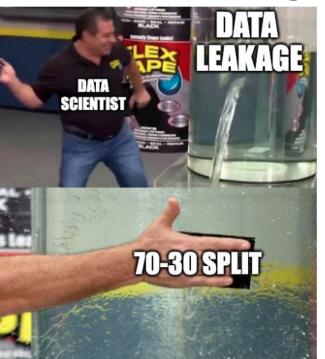


- Collaborating
- Debugging (remotely)





- Collaborating
- Debugging (remotely)
- Scientifically validating





- Collaborating
- Debugging (remotely)
- Scientifically validating
- Auditing





- Collaborating
- Debugging (remotely)
- Scientifically validating
- Auditing
- Legacy





How to accomplish reproducibility?



Four components to account for

WARNING

LOTS OF CODE AHEAD



1. Environment

```
# common pipenv commands
pipenv install --dev # install all deps in Pipfile
pipenv shell
pipenv run <command to run> # run without activating
```



2. Code

```
git clone https://github.com/tmthyjames/ds-meetup-ml-repro.git
git checkout -b <bre> <br
git add .
git commit -m "commit message"
git push origin <branch>
```



3. Data (data & model artifacts)

```
# common DVC commands
dvc remote add ...# link remote storage container to local code
dvc stage add ... # add stage for dvc to track
dvc dag
dvc repro
dvc push
```



4. Results (performance metrics)

```
# common DVC commands
$ dvc metrics show
       eval.json:
               AUC: 0.66729
               error: 0.16982
               TP: 516
$ dvc metrics diff
Path
          Metric
                    HEAD
                             workspace Change
eval.json ACU
                    0.65115
                             0.66729
                                       0.01614
eval.json error
                    0.1666
                             0.16982
                                       0.00322
eval.json TP
                                       -12
                    528
                             516
```



Let's walkthrough an example



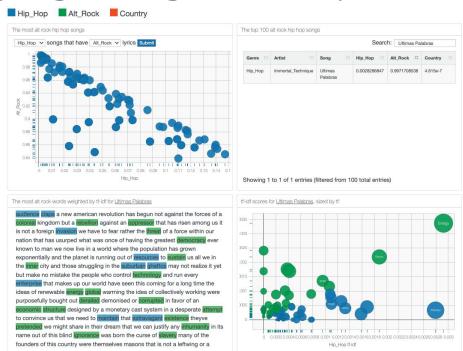
Predicting a song's genre given its lyrics



← Link to blog



← Link to code





Setting up the environment



Setting up the environment

```
git clone https://github.com/tmthyjames/ds-meetup-ml-repro.git
pipenv install --dev
pipenv run ipython kernel install --user --name=reproml
pipenv run python setup.py develop # to get access to the CLI
```



Creating the ETL pipeline using DVC

```
$ dvc stage add -n get-lyrics \
    -d reproml/etl/lyrics/_lyrics.py \
    -o data/raw/lyrics/ \
    reproml etl get-lyrics
$ dvc stage add -n prepro-lyrics \
    -d reproml/preprocess/_preprocess.py \
    -d data/raw/lyrics/ \
    -o data/processed/lyrics \
    reproml prepro process
```



Creating the modeling pipeline using DVC

```
$ dvc stage add -n split-lyrics \
    -d reproml/preprocess/_preprocess.py \
    -d data/raw/lyrics/ \
    -o data/modeling/train_set.parquet \
    -o data/modeling/test_set.parquet \
    reproml prepro split
$ dvc stage add -n train-model \
    -d data/modeling/train set.parquet \
    -d reproml/ml/_ml.py \
    -o model_artifacts/model.pkl \
    reproml ml train
```



Creating the validation stage using DVC

```
$ dvc stage add -n validate-model \
    -d model_artifacts/model.pkl \
    -d data/modeling/test_set.parquet \
    -m data/metrics/performance.json \
    reproml validate metrics
```



Now we can view our DAG

```
• • •
$ dvc dag
  | get-lyrics |
| prepro-lyrics |
 | split-lyrics |
  | train-model |
| validate-model |
```



Now DVC knows how to track our pipeline

- DVC will track changes
- DVC will add all tracked files to a remote storage
- DVC knows how to handle branches



Let's run the pipeline

```
• • •
$ dvc repro --force
Running stage 'get-lyrics':
> reproml etl get-lyrics
Running stage 'prepro-lyrics':
> reproml prepro process
Updating lock file 'dvc.lock'
Running stage 'split-lyrics':
> reproml prepro split
Updating lock file 'dvc.lock'
Running stage 'train-model':
> reproml ml train
Updating lock file 'dvc.lock'
Running stage 'validate-model':
> reproml validate metrics
Updating lock file 'dvc.lock'
To track the changes with git, run:
   git add dvc.lock
To enable auto staging, run:
   dvc config core.autostage true
Use `dvc push` to send your updates to remote storage.
```



Here's our model training code

```
. . .
import joblib
import pandas as pd
from sklearn.feature_extraction.text import (
   CountVectorizer,
   TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.pipeline import Pipeline
from reproml.config import ml_conf as mc
def train(
   srcpath: str = (
       mc.root path /
       mc.modeling_data_path /
        mc.train set.filename
   dstpath: str = mc.root_path / mc.model_artifact_path,
    train_df = pd.read_parquet(srcpath)
   text clf = Pipeline(
            ("vect", CountVectorizer()),
            ("clf", MultinomialNB(alpha=0.1))
   text_clf.fit(train_df["lyric"], train_df["ranker_genre"])
    joblib.dump(text_clf, dstpath)
```



We're going to change our training code

```
text clf = Pipeline(
                  ("vect", CountVectorizer()),
                  ("clf", MultinomialNB(alpha=0.1)) #
             text_clf = Pipeline(
                  ("vect", TfidfVectorizer()),
                  ("clf", MultinomialNB(alpha=0.1)) #
```



And rerun dvc repro

```
$ dvc repro
Stage 'get-lyrics' didn't change, skipping # notice these do not run again
Stage 'prepro-lyrics' didn't change, skipping # notice these do not run again
Stage 'split-lyrics' didn't change, skipping # notice these do not run again
Running stage 'train-model':
> reproml ml train
Running stage 'validate-model':
Updating lock file 'dvc.lock'
    git add dvc.lock
    dvc config core.autostage true
```



Now let's compare metrics

```
$ dvc metrics diff -- count-model tfidf-model
Path
                              Metric
                                         count-model
                                                        tfidf-model
                                                                       Change
data/metrics/performance.json
                                         0.6016
                                                        0.59422
                                                                       -0.00737
data/metrics/performance.json
                                         9753
                                                        9294
                                                                       -459
data/metrics/performance.json
                                         9753
                                                        9294
                                                                       -459
                             fps
data/metrics/performance.json precision
                                         0.6177
                                                        0.64136
                                                                       0.02366
data/metrics/performance.json recall
                                         0.60166
                                                        0.62041
                                                                       0.01875
data/metrics/performance.json
                                         14731
                                                        15190
                                                                       459
```



To close...

- 5 reasons to care about reproducibility in ML
 - o Collaboration, Debugging, Validation, Auditing, Legacy
- 4 components to account for
 - Environment, Code, Data, Metrics



Questions?



Code and slides on Github



Let's connect!

Timothy Dobbins



DATA SCIENTIST

Helping visionaries bring data products to market

