

The Model Review

improving transparency, reproducibility & knowledge sharing with MLflow



Jes Ford, PhD
ML Engineer at Cash App

Hi, Jes Ford here 🖐️

- Snowboarder 1st 🏂
- Originally from Alaska, currently living in Salt Lake City
- PhD in Physics 🔭
- Machine Learning Engineer (Modeler) at Cash App, Block
- Working on Natural Language Understanding for Customer Support

About this talk

- Why did my team decide to adopt a process for Model Review?
- What does Model Review mean?
- Our primary tool for review: MLflow
- Intro to MLflow
- How we are using MLflow to solve some of our problems

Motivation

Our team had recently doubled in size and was deploying lots of models.

But we had no good record keeping on what models exactly were in production, how they were trained, or what tricks or approaches were working well...

Motivation

What if a model needed to be retrained?

A new team member wants to build off the work that came before them?

What was the precision on that model supposed to be anyway?

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What was the precision on that model supposed to be anyway?

uhhh, let me see if I can find that notebook...

Goals for a new Model Review Process

1. **Transparency** and record keeping of what exactly is being deployed
2. **Reproducibility** of past experiments and ease of building off of them
3. **Knowledge Sharing** so we can learn from each other and new teammembers can get up to speed

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ALSO: We need to **automate** as much of this as possible!

Comparison to Code Review

Why do we Review Code?

- More 👁️ on code to spot bugs and potential issues
- Pull Requests create a record of changes/commits and also (ideally) documentation of changes, design decisions, trade-offs, etc.
- Knowledge sharing between teammates

Code vs Model Review *Similarities*

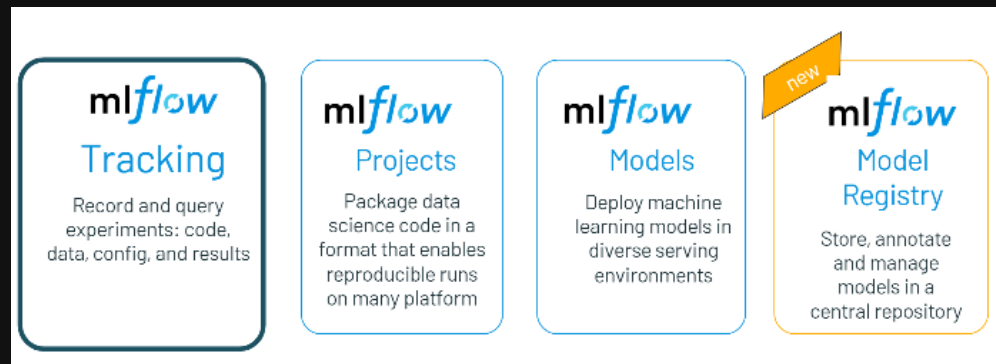
There is code involved.

Code vs Model Review *Differences*

- There is a lot of context beyond the Code Used to train a model
 - data, including any transformations
 - performance
 - entire ML process, including all your failed experiments
- We can't really review a model *just* by reading the final code
- Where to record async review comments? (GitHub not really a good fit for this)

What is MLflow?

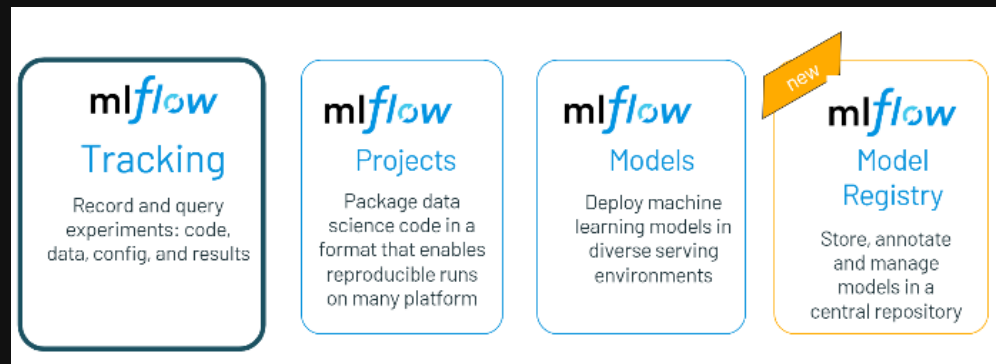
"Open source platform for managing the end-to-end machine learning lifecycle"



Language & library agnostic: includes APIs for Python, R, Java, but everything is accessible through a REST API & CLI, so it's very flexible for different use cases.

What is MLflow?

"Open source platform for managing the end-to-end machine learning lifecycle"



Language & library agnostic: includes APIs for Python, R, Java, but everything is accessible through a REST API & CLI, so it's very flexible for different use cases.

```
$ pip install mlflow
```

MLflow Tracking

Easily log almost anything you want to keep track of:

- parameters
- metrics
- arbitrary files ("artifacts" in mlflow)
 - such as plots, output files, Jupyter notebooks...
- code version

First Example

In [1]:

```
import mlflow

mlflow.log_param('my_parameter', 4)  # run starts automatically
mlflow.log_metric('score', 100)
mlflow.end_run()
```


MLflow Tracking



MLflow Tracking UI

```
$ mlflow ui
```

```
[2021-11-26 10:15:48 -0700] [19408] [INFO] Starting gunicorn 20.1.0
[2021-11-26 10:15:48 -0700] [19408] [INFO] Listening at: http://127.0.0.1:5000
(19408)
[2021-11-26 10:15:48 -0700] [19408] [INFO] Using worker: sync
[2021-11-26 10:15:48 -0700] [19411] [INFO] Booting worker with pid: 19411
```

MLflow Tracking UI

```
$ mlflow ui
```

```
[2021-11-26 10:15:48 -0700] [19408] [INFO] Starting gunicorn 20.1.0
[2021-11-26 10:15:48 -0700] [19408] [INFO] Listening at: http://127.0.0.1:5000
(19408)
[2021-11-26 10:15:48 -0700] [19408] [INFO] Using worker: sync
[2021-11-26 10:15:48 -0700] [19411] [INFO] Booting worker with pid: 19411
```

→ Go to <http://127.0.0.1:5000> in your browser...

MLflow

127.0.0.1:5000/#/

Search Experiments

Default

Default

Experiment ID: 0

Notes

Showing 1 matching run

Refresh

Compare

Delete

Download CSV

Start Time

All

Columns

Only show differences

metrics.rmse < 1 and params.model = "tree"

Search

Filter

Clear

								Metrics	Parameters
	Start Time	Duration	Run Name	User	Source	Version	Models	score	my_parameter
	12 minutes ago	10ms	-	jesford	ipykernel_launcher.py	-	-	100	4
Load more									

MLflow

127.0.0.1:5000/#/experiments/0/runs/b0fa1b8afaf04251b4a1a7d60dc7b6af

🔍

📄

☆

🔧

👤

⋮

mlflow


ExperimentsModels

GitHubDocs

Default > Run b0fa1b8afaf04251b4a1a7d60dc7b6af

Run b0fa1b8afaf04251b4a1a7d60dc7b6af

Date: 2021-11-26 10:24:51


Source:  ipykernel_launcher.py

User: jesford

Duration: 10ms

Status: FINISHED


Lifecycle Stage: active

▶ Notes 

▼ Parameters (1)

Name	Value
my_parameter	4

▼ Metrics (1)

Name	Value
score 	100

▶ Tags

▼ Artifacts

Logging Artifacts

In [2]:

```
import mlflow

# explicitly start the run to give it a nice name
mlflow.start_run(run_name='log-artifacts')

mlflow.log_param('my_parameter', 3)
mlflow.log_metric('score', 95)

with open('my_artifact.txt', 'w') as f:
    f.write('This is the contents of a file to be logged.')

mlflow.log_artifact('my_artifact.txt')

mlflow.end_run()
```

MLflow

127.0.0.1:5000/#/experiments/0

GitHub

Docs

mlflow

Experiments

Models

Default

Experiment ID: 0

Notes

Showing 2 matching runs

Refresh

Compare

Delete

Download CSV

Start Time

All

Columns

Only show differences

metrics.rmse < 1 and params.model = "tree"

Search

Filter

Clear

								Metrics	Parameters
	Start Time	Duration	Run Name	User	Source	Version	Models	score	my_parameter
	5 seconds ago	21ms	log-artifacts	jesford	ipykernel_launcher.py	-	-	95	3
	49 minutes ago	10ms	-	jesford	ipykernel_launcher.py	-	-	100	4
Load more									

MLflow

127.0.0.1:5000/#/experiments/0/runs/8aed6175a12a4d9aa604525ecb827052

mlflow


ExperimentsModels

GitHubDocs

Default > log-artifacts

log-artifacts

Date: 2021-11-26 11:14:38


Source:  ipykernel_launcher.py

User: jesford

Duration: 21ms

Status: FINISHED

Lifecycle Stage: active


▶ Notes 


▶ Parameters (1)

▶ Metrics (1)


▶ Tags

▼ Artifacts

 my_artifact.txt

Full Path:file:///Users/jesford/mlflow-tutorial/mlruns/0/8aed6175a12a4d9aa... 

Size: 44B



This is the contents of a file to be logged.

Where MLflow data is stored

By default your runs are recorded in files in a local `mlruns/` folder that gets created in your current working directory.

Lots of other options for local and remote tracking (the latter is best for teams / sharing results) - see [MLflow docs](#) for possibilities.

Not just for ML!

Notice that nothing we've done so far has been ML specific!

You could use MLFlow Tracking for kind of any analyses or projects where you find yourself manually recording values.

Tracking your ML Model

In [3]:

```
import mlflow
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, PrecisionRecallDisplay
from sklearn.model_selection import train_test_split
from sklearn.datasets import load_wine

# load and prepare data
data = load_wine()
binary_target = (data.target == 0).astype(int)
X_train, X_test, y_train, y_test = train_test_split(
    data.data, binary_target, test_size=0.33, shuffle=True, random_state=0,
)

with mlflow.start_run(run_name='wine-logreg'): # use context manager instead of start/end

    # fit a model with certain hyperparameters
    penalty = 'l2'
    max_iter = 10
    clf = LogisticRegression(penalty=penalty, max_iter=max_iter)
    clf.fit(X_train, y_train)

    # get predictions
    y_train_pred = clf.predict(X_train)
    y_test_pred = clf.predict(X_test)
    y_test_predprob = clf.predict_proba(X_test)[:, 1]

    # make a plot
    fig, ax = plt.subplots(1, 1)
    PrecisionRecallDisplay.from_predictions(y_test, y_test_predprob, ax=ax)
    fig.savefig('PR.png')

    # track all the things
```

```
mlflow.log_params({'penalty': penalty, 'max_iter': max_iter})
mlflow.log_metric('acc', accuracy_score(y_train, y_train_pred))
mlflow.log_metric('val_acc', accuracy_score(y_test, y_test_pred))
mlflow.log_artifact('PR.png')
mlflow.log_artifact('tutorial.ipynb')
mlflow.sklearn.log_model(clf, 'model')
```

/Users/jesford/anaconda3/envs/mlflow-demo/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py:818: ConvergenceWarning: lbfgs failed to converge (status=1):

STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

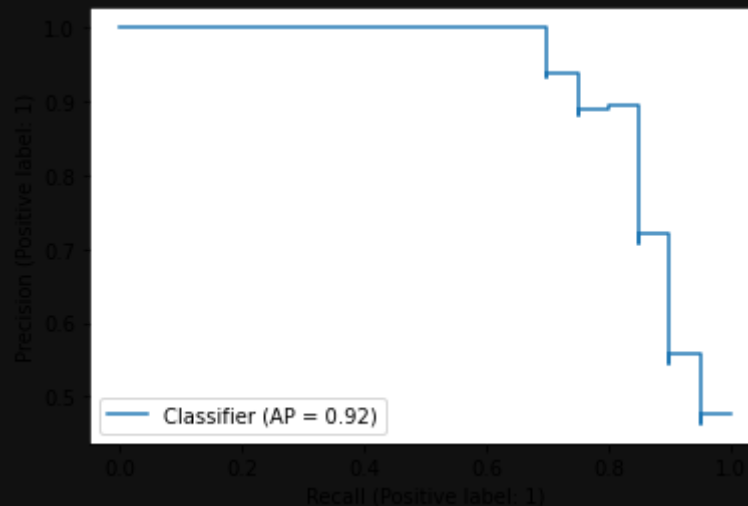
Increase the number of iterations (max_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html>

Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression

extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,



MLflow

127.0.0.1:5000/#/experiments/0/runs/9d50d41fedd6456cb8e967c45083100d

GitHub Docs

Default > wine-logreg

wine-logreg

Date: 2021-11-26 16:58:01

Source: `ipykernel_launcher.py`

User: jesford

Duration: 3.7s

Status: FINISHED

Lifecycle Stage: active

Notes

Parameters (2)

Name	Value
max_iter	10
penalty	l2

Metrics (2)

Name	Value
acc	0.924
val_acc	0.915

▼ Artifacts

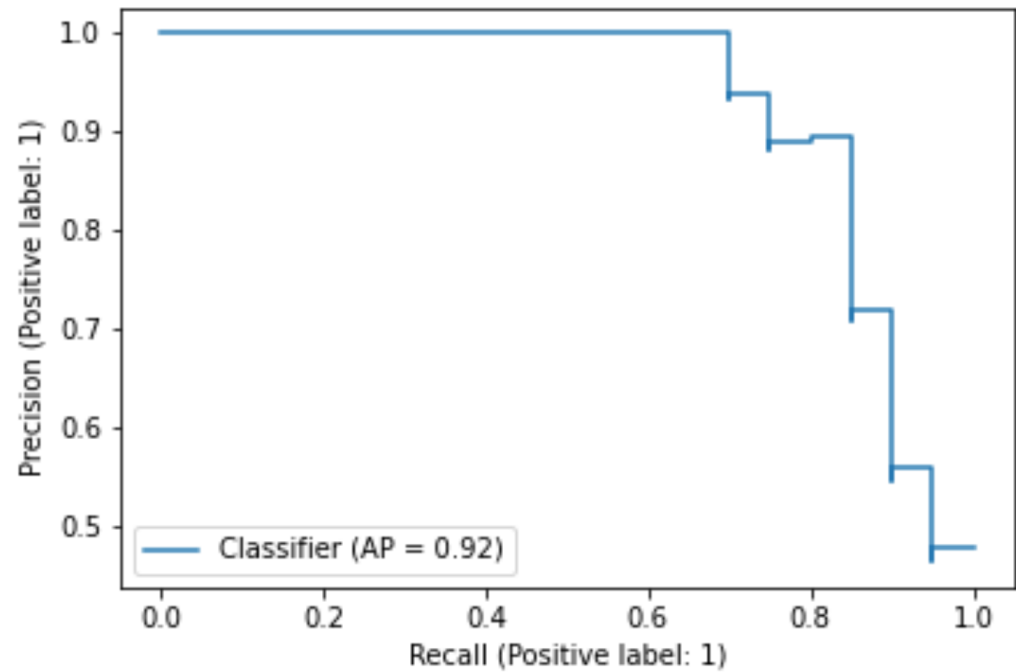
► model

PR.png

tutorial.ipynb

Full Path:file:///Users/jesford/mlflow-tutorial/mlruns/0/9d50d41fedd6456c...

Size: 9.15KB



▼ Artifacts

- ▼ model
- MLmodel
 - conda.yaml
 - model.pkl
 - requirements.txt
 - PR.png
 - tutorial.ipynb

Full Path:file:///Users/jesford/mlflow-tutorial/mlruns/0/9d50d41fedd6456c...

Register Model

MLflow Model

The code snippets below demonstrate how to make predictions using the logged model. You can also [register it to the model registry](#) to version control

Model schema

Input and output schema for your model. [Learn more](#)

Name	Type
No schema. See MLflow docs for how to include input and output schema with your model.	

Make Predictions

Predict on a Spark DataFrame:

```
import mlflow
logged_model = 'runs:/9d50d41fedd6456cb8e967c45083100d/model'

# Load model as a Spark UDF.
loaded_model = mlflow.pyfunc.spark_udf(spark, model_uri=logged_model)

# Predict on a Spark DataFrame.
columns = list(df.columns)
df.withColumn('predictions', loaded_model(*columns)).collect()
```

Predict on a Pandas DataFrame:

```
import mlflow
```

MLflow provides code snippets for loading & using the trained model via the mlflow API

Default > wine-logreg

wine-logreg



Date: 2021-11-26 16:58:01

Source: ipykernel_launcher.py

User: jesford

Duration: 3.7s

Status: FINISHED

Lifecycle Stage: active

▼ Notes

Wine Predictions

Details about my LogisticRegression model to predict wines...

▼ Parameters (2)

Name	Value
max_iter	10
penalty	l2

▼ Metrics (2)

Autologging Model Training

Autologging Model Training

A single line of code will automatically tracks lots of useful things about your model, metrics, plots.

Supported for `scikit-learn`, `tensorflow` & `keras`, `pytorch`, `xgboost`, and more.

Note: this is an "experimental" feature in MLflow!

Load & Prepare a Real World Dataset

"20 Newsgroups" dataset: text documents containing discussions of 20 different topics.

We'll just use 2 of these topics and build a binary classifier to distinguish between text that is about baseball vs hockey.

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In [4]:

```
from sklearn.datasets import fetch_20newsgroups
from sklearn.feature_extraction.text import TfidfVectorizer

# load train and test data for 2 categories
categories_to_classify = ['rec.sport.baseball', 'rec.sport.hockey']
X_train_raw, y_train = fetch_20newsgroups(
    subset='train', categories=categories_to_classify, return_X_y=True
)
X_test_raw, y_test = fetch_20newsgroups(
    subset='test', categories=categories_to_classify, return_X_y=True
)
# turn the text into numbers
vectorizer = TfidfVectorizer(max_features=5000)
X_train = vectorizer.fit_transform(X_train_raw).todense()
X_test = vectorizer.transform(X_test_raw).todense()

print('Training set size after TF-IDF transform: {}'.format(X_train.shape))
print('\nExample document:\n\n{}'.format(X_train_raw[0]))
```

```
Training set size after TF-IDF transform: (1197, 5000)
```

```
Example document:
```

```
From: dougb@comm.mot.com (Doug Bank)
```

Subject: Re: Info needed for Cleveland tickets
Reply-To: dougb@ecs.comm.mot.com
Organization: Motorola Land Mobile Products Sector
Distribution: usa
Nntp-Posting-Host: 145.1.146.35
Lines: 17

In article <1993Apr1.234031.4950@leland.Stanford.EDU>, bohnert@leland.Stan
ford.EDU (matthew bohnert) writes:

|> I'm going to be in Cleveland Thursday, April 15 to Sunday, April 18.
|> Does anybody know if the Tribe will be in town on those dates, and
|> if so, who're they playing and if tickets are available?

The tribe will be in town from April 16 to the 19th.
There are ALWAYS tickets available! (Though they are playing Toronto,
and many Toronto fans make the trip to Cleveland as it is easier to
get tickets in Cleveland than in Toronto. Either way, I seriously
doubt they will sell out until the end of the season.)

--

Doug Bank
dougb@ecs.comm.mot.com
dougb@nwu.edu
dougb@casbah.acns.nwu.edu

Private Systems Division
Motorola Communications Sector
Schaumburg, Illinois
708-576-8207

Autologging Example 1: sklearn

In [5]: `from sklearn.ensemble import RandomForestClassifier`

`mlflow.sklearn.autolog()` *# just one line added!*

```
rfc = RandomForestClassifier(n_estimators=10)
rfc.fit(X_train, y_train)
```

2021/11/27 15:57:24 WARNING mlflow.utils.autologging_utils: You are using an unsupported version of sklearn. If you encounter errors during autologging, try upgrading / downgrading sklearn to a supported version, or try upgrading MLflow.

2021/11/27 15:57:24 INFO mlflow.utils.autologging_utils: Created MLflow autologging run with ID '0767d058f4c34495901426d10fd4d8b0', which will track hyperparameters, performance metrics, model artifacts, and lineage information for the current sklearn workflow

/Users/jesford/anaconda3/envs/mlflow-demo/lib/python3.7/site-packages/sklearn/utils/validation.py:590: FutureWarning: np.matrix usage is deprecated in 1.0 and will raise a TypeError in 1.2. Please convert to a numpy array with np.asarray. For more information see: <https://numpy.org/doc/stable/reference/generated/numpy.matrix.html>

FutureWarning,

/Users/jesford/anaconda3/envs/mlflow-demo/lib/python3.7/site-packages/sklearn/utils/validation.py:590: FutureWarning: np.matrix usage is deprecated in 1.0 and will raise a TypeError in 1.2. Please convert to a numpy array with np.asarray. For more information see: <https://numpy.org/doc/stable/reference/generated/numpy.matrix.html>

FutureWarning,

/Users/jesford/anaconda3/envs/mlflow-demo/lib/python3.7/site-packages/skle

arn/utils/validation.py:590: FutureWarning: np.matrix usage is deprecated in 1.0 and will raise a TypeError in 1.2. Please convert to a numpy array with np.asarray. For more information see: <https://numpy.org/doc/stable/reference/generated/numpy.matrix.html>

FutureWarning,

2021/11/27 15:57:25 WARNING mlflow.utils.autologging_utils: MLflow autologging encountered a warning: "/Users/jesford/anaconda3/envs/mlflow-demo/lib/python3.7/site-packages/sklearn/utils/deprecation.py:87: FutureWarning: Function plot_confusion_matrix is deprecated; Function `plot_confusion_matrix` is deprecated in 1.0 and will be removed in 1.2. Use one of the class methods: ConfusionMatrixDisplay.from_predictions or ConfusionMatrixDisplay.from_estimator."

/Users/jesford/anaconda3/envs/mlflow-demo/lib/python3.7/site-packages/sklearn/utils/validation.py:590: FutureWarning: np.matrix usage is deprecated in 1.0 and will raise a TypeError in 1.2. Please convert to a numpy array with np.asarray. For more information see: <https://numpy.org/doc/stable/reference/generated/numpy.matrix.html>

FutureWarning,

2021/11/27 15:57:25 WARNING mlflow.utils.autologging_utils: MLflow autologging encountered a warning: "/Users/jesford/anaconda3/envs/mlflow-demo/lib/python3.7/site-packages/sklearn/utils/deprecation.py:87: FutureWarning: Function plot_roc_curve is deprecated; Function `plot_roc_curve` is deprecated in 1.0 and will be removed in 1.2. Use one of the class methods: RocCurveDisplay.from_predictions or RocCurveDisplay.from_estimator."

/Users/jesford/anaconda3/envs/mlflow-demo/lib/python3.7/site-packages/sklearn/utils/validation.py:590: FutureWarning: np.matrix usage is deprecated in 1.0 and will raise a TypeError in 1.2. Please convert to a numpy array with np.asarray. For more information see: <https://numpy.org/doc/stable/reference/generated/numpy.matrix.html>

FutureWarning,

2021/11/27 15:57:25 WARNING mlflow.utils.autologging_utils: MLflow autologging encountered a warning: "/Users/jesford/anaconda3/envs/mlflow-demo/lib/python3.7/site-packages/sklearn/utils/deprecation.py:87: FutureWarning:


```
Function plot_precision_recall_curve is deprecated; Function `plot_precision_recall_curve` is deprecated in 1.0 and will be removed in 1.2. Use one of the class methods: PrecisionRecallDisplay.from_predictions or PrecisionRecallDisplay.from_estimator."
```

```
/Users/jesford/anaconda3/envs/mlflow-demo/lib/python3.7/site-packages/sklearn/utils/validation.py:590: FutureWarning: np.matrix usage is deprecated in 1.0 and will raise a TypeError in 1.2. Please convert to a numpy array with np.asarray. For more information see: https://numpy.org/doc/stable/reference/generated/numpy.matrix.html
```

```
FutureWarning,
```

```
/Users/jesford/anaconda3/envs/mlflow-demo/lib/python3.7/site-packages/sklearn/utils/validation.py:590: FutureWarning: np.matrix usage is deprecated in 1.0 and will raise a TypeError in 1.2. Please convert to a numpy array with np.asarray. For more information see: https://numpy.org/doc/stable/reference/generated/numpy.matrix.html
```


```
FutureWarning,
```

```
/Users/jesford/anaconda3/envs/mlflow-demo/lib/python3.7/site-packages/sklearn/utils/validation.py:590: FutureWarning: np.matrix usage is deprecated in 1.0 and will raise a TypeError in 1.2. Please convert to a numpy array with np.asarray. For more information see: https://numpy.org/doc/stable/reference/generated/numpy.matrix.html
```


```
FutureWarning,
```

```
Out[5]: RandomForestClassifier(n_estimators=10)
```

Back in the MLflow UI...


 [Experiments](#) [Models](#) [GitHub](#) [Docs](#)

Default > Run 360f48f82d954f32a97216d78a7993dc

Run 360f48f82d954f32a97216d78a7993dc 

Date: 2021-11-27 14:48:28


Duration: 3.8s

Source:  ipykernel_launcher.py

Status: FINISHED

User: jesford

Lifecycle Stage: active

▶ Notes 

▼ Parameters (18)

Name	Value
bootstrap	True
ccp_alpha	0.0
class_weight	None
criterion	gini
max_depth	None
max_features	auto
max_leaf_nodes	None
max_samples	None
min_impurity_decrease	0.0
min_samples_leaf	1

min_samples_split	2
min_weight_fraction_leaf	0.0
n_estimators	10
n_jobs	None
oob_score	False
random_state	None
verbose	0
warm_start	False

▼ Metrics (7)

Name	Value
training_accuracy_score 🔗	0.997
training_f1_score 🔗	0.997
training_log_loss 🔗	0.081
training_precision_score 🔗	0.997
training_recall_score 🔗	0.997
training_roc_auc_score 🔗	1
training_score 🔗	0.997

We see all RF hyperparameters (even those we didn't set explicitly) are recorded...

... as well as some default training metrics (would have to log validation metrics manually since `.fit` doesn't know about them)

... and we get some really useful plots out of the box!

▼ Artifacts

▼ model

MLmodel

conda.yaml

model.pkl

requirements.txt

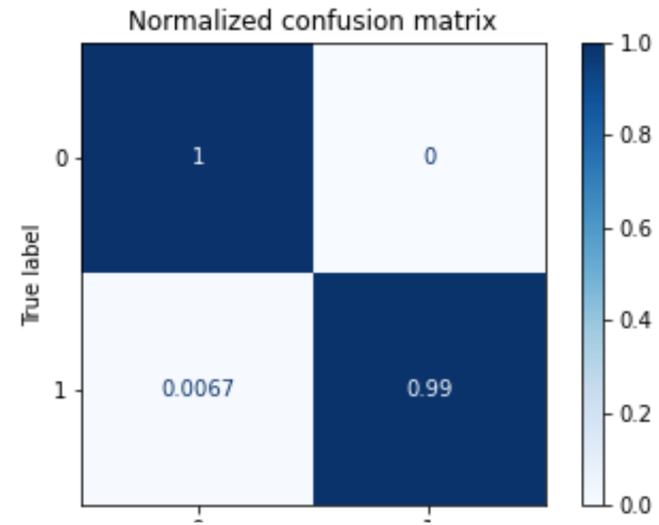
training_confusion_matrix.png

training_precision_recall_curve.png

training_roc_curve.png

Full Path:file:///Users/jesford/mlflow-tutorial/mlruns/0/360f48f82d954f32a97216d78a7993dc/artifacts/training_confusion_matrix.png

Size: 8.6KB



Autologging Example 2:

tensorflow.keras

In [6]:

```
import tensorflow as tf
from tensorflow.keras import Input, Model, layers

with mlflow.start_run(run_name='hockey-vs-baseball-NN'):

    mlflow.tensorflow.autolog() # just one line added!

    # parameters to vary
    hidden_layer_size = 16
    learning_rate = 0.1

    # a simple NN with one hidden layer
    inputs = Input(shape=(X_train.shape[1],))
    x = layers.Dense(hidden_layer_size, activation='relu')(inputs)
    outputs = layers.Dense(1, activation='sigmoid')(x)
    model = Model(inputs, outputs)

    loss = 'binary_crossentropy'
    optimizer = tf.optimizers.SGD(learning_rate=learning_rate)
    metrics = [
        tf.metrics.BinaryAccuracy(),
        tf.metrics.AUC(curve='ROC', name='AUROC'),
    ]
    model.compile(optimizer=optimizer, loss=loss, metrics=metrics)

    model.fit(X_train, y_train, epochs=40, shuffle=True, validation_data=(X_test, y_test))
```

```
2021-11-27 15:57:29.940299: I tensorflow/core/platform/cpu_feature_guard.c
c:145] This TensorFlow binary is optimized with Intel(R) MKL-DNN to use th
```

e following CPU instructions in performance critical operations: SSE4.1 SSE4.2 AVX AVX2 FMA

To enable them in non-MKL-DNN operations, rebuild TensorFlow with the appropriate compiler flags.

```
2021-11-27 15:57:29.940539: I tensorflow/core/common_runtime/process_util.cc:115] Creating new thread pool with default inter op setting: 4. Tune using inter_op_parallelism_threads for best performance.
```

Train on 1197 samples, validate on 796 samples

Epoch 1/40

864/1197 [=====>.....] - ETA: 1s - loss: 0.6932 - binary_accuracy: 0.5000 - AUROC: 0.4967

```
2021-11-27 15:57:32.775138: I tensorflow/core/profiler/lib/profiler_session.cc:184] Profiler session started.
```

1197/1197 [=====] - 3s 3ms/sample - loss: 0.6927 - binary_accuracy: 0.5138 - AUROC: 0.5178 - val_loss: 0.6923 - val_binary_accuracy: 0.5038 - val_AUROC: 0.5648

Epoch 2/40

1197/1197 [=====] - 0s 407us/sample - loss: 0.6885 - binary_accuracy: 0.5556 - AUROC: 0.6514 - val_loss: 0.6881 - val_binary_accuracy: 0.6583 - val_AUROC: 0.7370

Epoch 3/40

1197/1197 [=====] - 1s 508us/sample - loss: 0.6823 - binary_accuracy: 0.6942 - AUROC: 0.8035 - val_loss: 0.6834 - val_binary_accuracy: 0.6118 - val_AUROC: 0.8632

Epoch 4/40

1197/1197 [=====] - 0s 372us/sample - loss: 0.6742 - binary_accuracy: 0.7853 - AUROC: 0.8988 - val_loss: 0.6772 - val_binary_accuracy: 0.6093 - val_AUROC: 0.9249

Epoch 5/40

1197/1197 [=====] - 1s 477us/sample - loss: 0.6647 - binary_accuracy: 0.8755 - AUROC: 0.9448 - val_loss: 0.6685 - val_binary_accuracy: 0.7853 - val_AUROC: 0.9448

y_accuracy: 0.8894 - val_AUROC: 0.9536
Epoch 6/40
1197/1197 [=====] - 1s 500us/sample - loss: 0.6514 - binary_accuracy: 0.8881 - AUROC: 0.9638 - val_loss: 0.6623 - val_binary_accuracy: 0.5239 - val_AUROC: 0.9693
Epoch 7/40
1197/1197 [=====] - 1s 420us/sample - loss: 0.6381 - binary_accuracy: 0.8688 - AUROC: 0.9742 - val_loss: 0.6469 - val_binary_accuracy: 0.9146 - val_AUROC: 0.9752
Epoch 8/40
1197/1197 [=====] - 0s 333us/sample - loss: 0.6185 - binary_accuracy: 0.9206 - AUROC: 0.9831 - val_loss: 0.6327 - val_binary_accuracy: 0.9058 - val_AUROC: 0.9774
Epoch 9/40
1197/1197 [=====] - 1s 492us/sample - loss: 0.5967 - binary_accuracy: 0.9532 - AUROC: 0.9926 - val_loss: 0.6161 - val_binary_accuracy: 0.8555 - val_AUROC: 0.9809
Epoch 10/40
1197/1197 [=====] - 1s 440us/sample - loss: 0.5707 - binary_accuracy: 0.9674 - AUROC: 0.9948 - val_loss: 0.5978 - val_binary_accuracy: 0.8028 - val_AUROC: 0.9823
Epoch 11/40
1197/1197 [=====] - 0s 341us/sample - loss: 0.5412 - binary_accuracy: 0.9524 - AUROC: 0.9939 - val_loss: 0.5704 - val_binary_accuracy: 0.9384 - val_AUROC: 0.9830
Epoch 12/40
1197/1197 [=====] - 0s 388us/sample - loss: 0.5076 - binary_accuracy: 0.9657 - AUROC: 0.9961 - val_loss: 0.5457 - val_binary_accuracy: 0.9196 - val_AUROC: 0.9838
Epoch 13/40
1197/1197 [=====] - 1s 698us/sample - loss: 0.4711 - binary_accuracy: 0.9716 - AUROC: 0.9959 - val_loss: 0.5161 - val_binary_accuracy: 0.9121 - val_AUROC: 0.9851

Epoch 14/40
1197/1197 [=====] - 1s 433us/sample - loss: 0.432
3 - binary_accuracy: 0.9758 - AUROC: 0.9974 - val_loss: 0.4851 - val_binar
y_accuracy: 0.9460 - val_AUROC: 0.9856
Epoch 15/40
1197/1197 [=====] - 0s 410us/sample - loss: 0.394
7 - binary_accuracy: 0.9733 - AUROC: 0.9979 - val_loss: 0.4630 - val_binar
y_accuracy: 0.9146 - val_AUROC: 0.9860
Epoch 16/40
1197/1197 [=====] - 0s 363us/sample - loss: 0.358
8 - binary_accuracy: 0.9816 - AUROC: 0.9980 - val_loss: 0.4260 - val_binar
y_accuracy: 0.9472 - val_AUROC: 0.9869
Epoch 17/40
1197/1197 [=====] - 1s 446us/sample - loss: 0.323
0 - binary_accuracy: 0.9766 - AUROC: 0.9985 - val_loss: 0.4081 - val_binar
y_accuracy: 0.9008 - val_AUROC: 0.9875
Epoch 18/40
1197/1197 [=====] - 0s 387us/sample - loss: 0.293
3 - binary_accuracy: 0.9749 - AUROC: 0.9985 - val_loss: 0.3729 - val_binar
y_accuracy: 0.9485 - val_AUROC: 0.9880
Epoch 19/40
1197/1197 [=====] - 1s 463us/sample - loss: 0.264
2 - binary_accuracy: 0.9841 - AUROC: 0.9990 - val_loss: 0.3501 - val_binar
y_accuracy: 0.9497 - val_AUROC: 0.9886
Epoch 20/40
1197/1197 [=====] - 1s 477us/sample - loss: 0.239
7 - binary_accuracy: 0.9891 - AUROC: 0.9993 - val_loss: 0.3304 - val_binar
y_accuracy: 0.9485 - val_AUROC: 0.9891
Epoch 21/40
1197/1197 [=====] - 0s 352us/sample - loss: 0.216
5 - binary_accuracy: 0.9891 - AUROC: 0.9991 - val_loss: 0.3101 - val_binar
y_accuracy: 0.9447 - val_AUROC: 0.9896
Epoch 22/40

1197/1197 [=====] - 0s 358us/sample - loss: 0.196
8 - binary_accuracy: 0.9866 - AUROC: 0.9994 - val_loss: 0.3046 - val_binary_accuracy: 0.9234 - val_AUROC: 0.9900
Epoch 23/40
1197/1197 [=====] - 0s 340us/sample - loss: 0.178
8 - binary_accuracy: 0.9908 - AUROC: 0.9995 - val_loss: 0.2832 - val_binary_accuracy: 0.9560 - val_AUROC: 0.9903
Epoch 24/40
1197/1197 [=====] - 0s 336us/sample - loss: 0.164
9 - binary_accuracy: 0.9925 - AUROC: 0.9997 - val_loss: 0.2640 - val_binary_accuracy: 0.9523 - val_AUROC: 0.9906
Epoch 25/40
1197/1197 [=====] - 0s 345us/sample - loss: 0.151
6 - binary_accuracy: 0.9925 - AUROC: 0.9998 - val_loss: 0.2530 - val_binary_accuracy: 0.9447 - val_AUROC: 0.9908
Epoch 26/40
1197/1197 [=====] - 0s 345us/sample - loss: 0.140
5 - binary_accuracy: 0.9925 - AUROC: 0.9997 - val_loss: 0.2417 - val_binary_accuracy: 0.9485 - val_AUROC: 0.9911
Epoch 27/40
1197/1197 [=====] - 0s 338us/sample - loss: 0.129
3 - binary_accuracy: 0.9958 - AUROC: 0.9998 - val_loss: 0.2332 - val_binary_accuracy: 0.9598 - val_AUROC: 0.9914
Epoch 28/40
1197/1197 [=====] - 0s 343us/sample - loss: 0.120
8 - binary_accuracy: 0.9958 - AUROC: 0.9999 - val_loss: 0.2232 - val_binary_accuracy: 0.9485 - val_AUROC: 0.9917
Epoch 29/40
1197/1197 [=====] - 0s 348us/sample - loss: 0.112
2 - binary_accuracy: 0.9958 - AUROC: 0.9999 - val_loss: 0.2139 - val_binary_accuracy: 0.9548 - val_AUROC: 0.9919
Epoch 30/40
1197/1197 [=====] - 1s 455us/sample - loss: 0.104


7 - binary_accuracy: 0.9950 - AUROC: 0.9999 - val_loss: 0.2087 - val_binary_accuracy: 0.9472 - val_AUROC: 0.9921
Epoch 31/40
1197/1197 [=====] - 0s 350us/sample - loss: 0.0978 - binary_accuracy: 0.9958 - AUROC: 0.9999 - val_loss: 0.2000 - val_binary_accuracy: 0.9560 - val_AUROC: 0.9923
Epoch 32/40
1197/1197 [=====] - 1s 545us/sample - loss: 0.0923 - binary_accuracy: 0.9975 - AUROC: 0.9999 - val_loss: 0.1935 - val_binary_accuracy: 0.9560 - val_AUROC: 0.9926
Epoch 33/40
1197/1197 [=====] - 0s 398us/sample - loss: 0.0867 - binary_accuracy: 0.9958 - AUROC: 1.0000 - val_loss: 0.1883 - val_binary_accuracy: 0.9560 - val_AUROC: 0.9928
Epoch 34/40
1197/1197 [=====] - 1s 483us/sample - loss: 0.0816 - binary_accuracy: 0.9983 - AUROC: 1.0000 - val_loss: 0.1827 - val_binary_accuracy: 0.9585 - val_AUROC: 0.9930
Epoch 35/40
1197/1197 [=====] - 1s 510us/sample - loss: 0.0768 - binary_accuracy: 0.9992 - AUROC: 1.0000 - val_loss: 0.1781 - val_binary_accuracy: 0.9548 - val_AUROC: 0.9931
Epoch 36/40
1197/1197 [=====] - 1s 483us/sample - loss: 0.0729 - binary_accuracy: 0.9992 - AUROC: 1.0000 - val_loss: 0.1735 - val_binary_accuracy: 0.9585 - val_AUROC: 0.9933
Epoch 37/40
1197/1197 [=====] - 1s 493us/sample - loss: 0.0689 - binary_accuracy: 0.9992 - AUROC: 1.0000 - val_loss: 0.1700 - val_binary_accuracy: 0.9648 - val_AUROC: 0.9934
Epoch 38/40
1197/1197 [=====] - 1s 484us/sample - loss: 0.0659 - binary_accuracy: 0.9992 - AUROC: 1.0000 - val_loss: 0.1662 - val_binary_accuracy: 0.9648 - val_AUROC: 0.9934

```
y_accuracy: 0.9648 - val_AUROC: 0.9935
Epoch 39/40
1197/1197 [=====] - 1s 454us/sample - loss: 0.061
6 - binary_accuracy: 0.9992 - AUROC: 1.0000 - val_loss: 0.1638 - val_binar
y_accuracy: 0.9636 - val_AUROC: 0.9936
Epoch 40/40
1197/1197 [=====] - 1s 483us/sample - loss: 0.059
1 - binary_accuracy: 0.9992 - AUROC: 1.0000 - val_loss: 0.1598 - val_binar
y_accuracy: 0.9661 - val_AUROC: 0.9938
WARNING:tensorflow:From /Users/jesford/anaconda3/envs/mlflow-demo/lib/python
on3.7/site-packages/tensorflow_core/python/ops/resource_variable_ops.py:17
81: calling BaseResourceVariable.__init__ (from tensorflow.python.ops.reso
urce_variable_ops) with constraint is deprecated and will be removed in a
future version.
Instructions for updating:
If using Keras pass *_constraint arguments to layers.
```

```
2021-11-27 15:57:54.053267: W tensorflow/python/util/util.cc:299] Sets are
not currently considered sequences, but this may change in the future, so
consider avoiding using them.
```

```
INFO:tensorflow:Assets written to: /var/folders/xv/48y52h7j27g9jp0vs5n4s8r
c0000gn/T/tmp411rgnb/model/data/model/assets
```


Again, all the parameters & metrics relevant to the run are recorded automatically

 Experiments Models GitHub Docs

Default > hockey-vs-baseball-NN

hockey-vs-baseball-NN

Date: 2021-11-27 14:49:19


Source:  ipykernel_launcher.py

User: jesford

Duration: 28.3s

Status: FINISHED

Lifecycle Stage: active




▶ Notes 

▼ Parameters (19)

Name	Value
batch_size	None
class_weight	None
epochs	40
initial_epoch	0
kwargs	<class 'inspect_empty'>
max_queue_size	10
opt_decay	0.0
opt_learning_rate	0.1

opt_momentum	0.0
opt_name	SGD
opt_nesterov	False
sample_weight	None
shuffle	True
steps_per_epoch	None
use_multiprocessing	False
validation_freq	1
validation_split	0.0
validation_steps	None
workers	1

▼ Metrics (6)

Name	Value
AUROC 	1
binary_accuracy 	0.999
loss 	0.058

▼ Metrics (6)

Name	Value
AUROC	1
binary_accuracy	0.999
loss	0.058
val_AUROC	0.994
val_binary_accuracy	0.966
val_loss	0.156

► Tags

▼ Artifacts

▼ model

▼ data

► model

- keras_module.txt
- save_format.txt
- MLmodel
- conda.yaml
- requirements.txt

► tensorboard_logs

model_summary.txt

Full Path:file:///Users/jesford/mlflow-tutorial/mlruns/0/bb82e09018b4473dbc774b5e3033198...

Size: 744B

Model: "model"

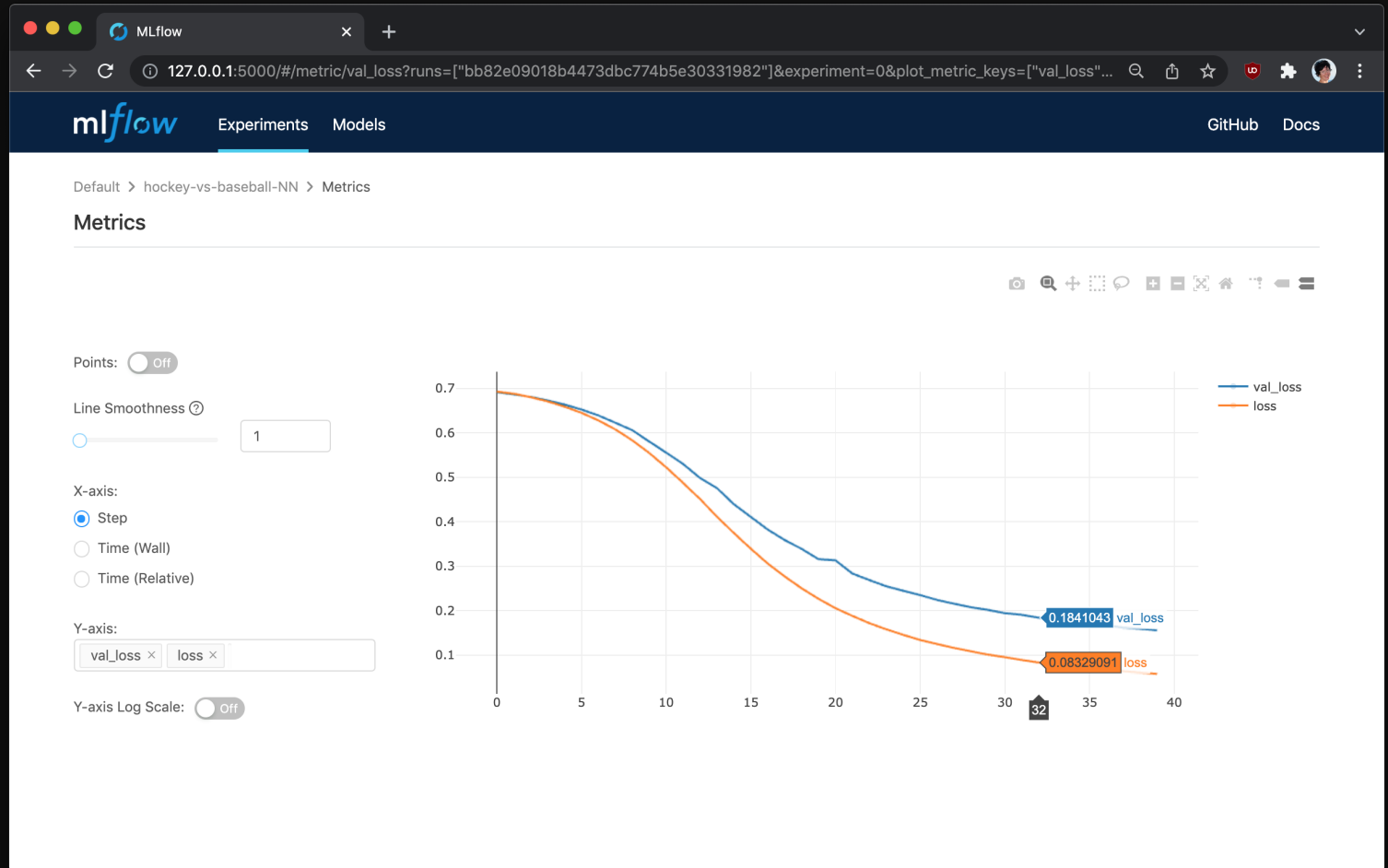
Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 5000)]	0
dense (Dense)	(None, 16)	80016
dense_1 (Dense)	(None, 1)	17

Total params: 80,033

Notice model summary, tensorboard logs, and the TF saved model

Note: our team uses this saved model artifact (the inner model folder) directly for deployment, since our infrastructure isn't yet set up to deploy from MLflow directly.

Clicking into one of the metrics, we can view training curves



Powerful features for comparing lots of models

Suppose you had run many iterations of this small NN with different hyperparameters...

Powerful features for comparing lots of models

Suppose you had run many iterations of this small NN with different hyperparameters...

In the UI you can sort by metrics

Default

Experiment ID: 0

Notes

Showing 9 matching runs

Refresh

Compare

Delete

Download CSV

↓ val_binary_accuracy

All



Columns

Only show differences



tags."mlflow.runName" = 'hockey-vs-baseball-NI

Search



Filter

Clear

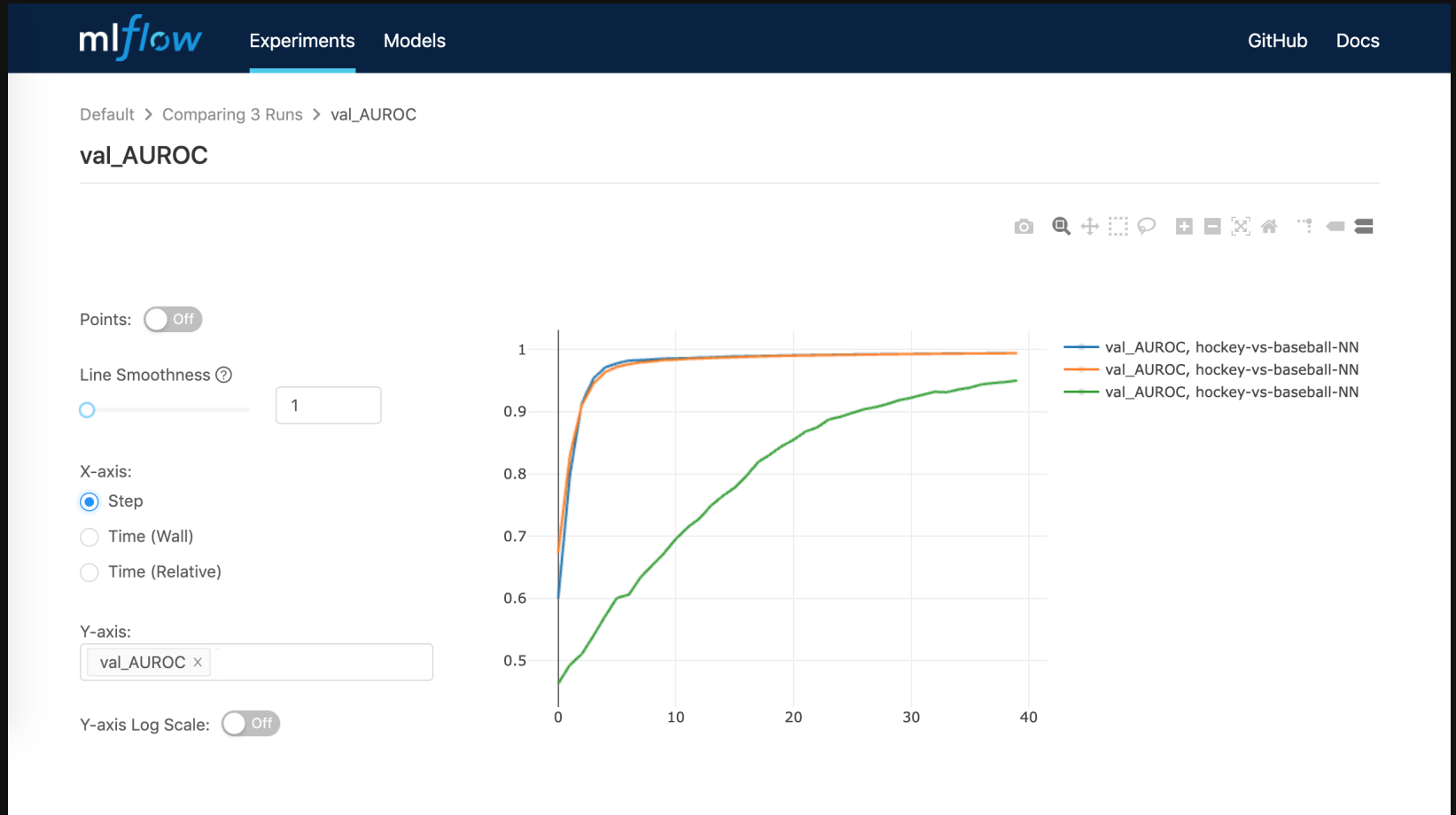
			Metrics							Parameters
<input type="checkbox"/>	Start Time	Run Name	Models	AUROC	binary_accuracy	loss	val_AUROC	↓ val_binary_accuracy	val_loss	opt_learning_rate
<input type="checkbox"/>	✓ 45 minut	hockey-vs-baseball-NN	keras	1	0.999	0.058	0.994	0.966	0.156	0.1
<input type="checkbox"/>	✓ 7 minute	hockey-vs-baseball-NN	keras	1	0.999	0.056	0.994	0.964	0.161	0.1
<input type="checkbox"/>	✓ 10 minut	hockey-vs-baseball-NN	keras	1	0.999	0.071	0.993	0.964	0.17	0.1
<input type="checkbox"/>	✓ 6 minute	hockey-vs-baseball-NN	keras	1	0.999	0.056	0.994	0.961	0.153	0.1
<input type="checkbox"/>	✓ 7 minute	hockey-vs-baseball-NN	keras	1	0.999	0.059	0.994	0.961	0.158	0.1
<input type="checkbox"/>	✓ 8 minute	hockey-vs-baseball-NN	keras	0.987	0.931	0.656	0.95	0.883	0.666	0.01
<input type="checkbox"/>	✓ 9 minute	hockey-vs-baseball-NN	keras	0.895	0.852	0.686	0.84	0.817	0.688	0.01
<input type="checkbox"/>	✓ 8 minute	hockey-vs-baseball-NN	keras	0.609	0.53	0.692	0.578	0.533	0.692	0.001
<input type="checkbox"/>	✓ 9 minute	hockey-vs-baseball-NN	keras	0.622	0.553	0.691	0.603	0.533	0.691	0.001

... you also view run details side-by-side

By selecting a few checkboxes and clicking the "Compare" button. Notice parameter differences are highlighted!

... and plot training curves from different runs

Similar to TensorBoard.



Incorporating MLflow into our Model Review Process

Step 1: Training Infrastructure

Create/maintain a reasonably-flexibly **common training infrastructure** that works for *most* of our team's problems.

Step 2: MLflow Tracking

MLflow Tracking is embedded in this infrastructure, so experiment record-keeping happens automatically:

- all training parameters & settings
- train and test metrics
- environment: the docker image, code version, the training script or notebook itself
- model (and related artifacts needed for deployment)
- common plots and results of analyses that help us understand performance

Step 3: Use Notes for Context

MLflow UI Markdown Notes section used for all the context that can't be recorded automatically:

- business requirements, e.g. links to any project docs
- things we tried that didn't work
- describe any non-standard treatment of the data
- decisions or trade-offs made along the way
- if shadow deployed, any observations on live data
- anything you'd want to know if you were picking up the project from scratch

Step 4: Model Review

Prior to Live Launch of a new model, trigger a **Model Review**:

- make sure all "required" fields were tracked and fill out the Notes section
- request a primary and secondary reviewer and send them the link to the MLflow run
- reviewers expected to review the MLflow run & related code async
- schedule a 30min *synchronous* review, other team members invited as optional
- meeting is to discuss, ask questions, make suggestions (rarely to block deployment)

Back to our Goals for Model Review

1. **Transparency** is achieved by having shareable links to all the training details.
2. **Reproducibility** is improved by recording everything needed to re-create a training run.
3. **Knowledge Sharing** happens through the review process or simply by sharing MLflow examples with colleagues.

MLflow is helpful for this because we can view so many details about the model in one place.

Summary

- We improved model deployment record keeping by integrating MLflow tracking into our shared training infrastructure.
- MLflow is a lightweight and powerful way to track your ML experiments
 - adding one line of code (autologging) can get you a long way!
 - we only talked about Tracking here (see also: MLflow Projects, Models, Model Registry)
- Our review "process" is a WIP! I'd *really* love to talk to anyone who has different processes in place for things like this!

Questions? 🤔

This notebook presentation is on GitHub: <https://github.com/jesford/model-review>