## Model Monitoring

MLflow, Tensorboard, Weights & Biases

Credit to TA.Cheetah & TA.Phu

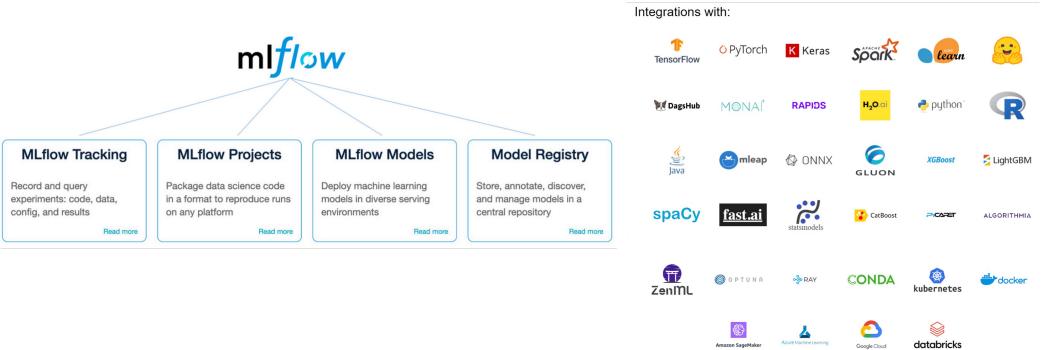
## Outline

- MLflow
- Tensorboard
- Weights & Biases

## **MLflow**

#### What is MLflow?

MLflow makes it simple to construct end-to-end Machine Learning pipelines in production, and this
article will teach you all you need to know about the platform. This implies that at the conclusion of
this tutorial, you'll be able to utilize MLflow for Machine Learning pipelines from model
experimentation through model deployment.



#### How to run MLflow

Install mlflow

```
!pip install mlflow --quiet
```

#### Import libraries

```
# Importing all Libraries
import mlflow
import mlflow.sklearn

import numpy as np
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report
Python
```

#### Load dataset and define evaluation metrics

```
# Load and split dataset
X, Y = load_breast_cancer(return_X_y=True)
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=0)
print("Training Data Shape: ", X_train.shape, y_train.shape)
print("Testing Data Shape: ", X_test.shape, y_test.shape)

def eval_metrics(actual, pred):
    accuracy = accuracy_score(actual, pred)
    return accuracy
```

## **Model tracking**

- 1. Start an experiment using **mlflow.start\_run()** which switches the context of your existing model code to enable mlflow tracking.
- 2. We log the run parameters with mlflow.log\_param()
- 3. We log the model metrics (mean accuracy on the training set in this case) with mlflow.log\_metric().
- 4. After model training and evaluation, I have logged the model using mlflow.sklearn.log\_model().

```
def train_model(criterion, max_depth):
    # Starting the Experiement
    with mlflow.start run():
        # Model building
        model = DecisionTreeClassifier(criterion=criterion, max depth=max depth,random state=0)
        model.fit(X train, y train) # Model Training
       y pred = model.predict(X test) # Model Prediction on Testing data
        (accuracy) = eval metrics(y test, y pred)
        print('Decirion tree (criterion=%s, max_depth=%d):'%(criterion, max_depth))
        print('Accuracy: {:.4f}'.format(accuracy))
        # Logging Parameters
        mlflow.log param("criterion", criterion)
        mlflow.log_param("max_depth", max_depth)
        # Logging Metrics
        mlflow.log_metric("accuracy", accuracy_score(y_test, y_pred))
        # Model Logging
        mlflow.sklearn.log model(model, 'model') #input example=input example)
        return model
```

#### Train model and search best 5 runs

Train 10 models with different hyperparameters

INFO [alembic.runtime.migration] Context impl SQLiteImpl.
INFO [alembic.runtime.migration] Will assume non-transactional DDL.

artifact_uri	start_time	end_time	metrics.accuracy	params.max_depth	params.criterion	tags.mlflow.sour
./mlruns/1/5d63abf908a643ac93724bd076496e19/ar	2023-08-23 01:47:10.328000+00:00	2023-08-23 01:47:10.584000+00:00	0.964912	3	gini	/usr/local/lib/python3 packages
./mlruns/1/d845b4259e634b5cb8485012cc6bc01b/ar	2023-08-23 01:47:10.014000+00:00	2023-08-23 01:47:10.263000+00:00	0.964912	2	gini	/usr/local/lib/python3 packages
./mlruns/1/4746bcfe0a5b4936b3350514515e0536/ar	2023-08-23 01:47:10.639000+00:00	2023-08-23 01:47:10.961000+00:00	0.956140	4	gini	/usr/local/lib/python3 packages
./mlruns/1/09ad160ad4734e68a6044e59228c805a/ar	2023-08-23 01:47:11.931000+00:00	2023-08-23 01:47:12.131000+00:00	0.947368	3	entropy	/usr/local/lib/python3 packages
./mlruns/1/d16fe0518d2d4bff80f343f9a58be6b4/ar	2023-08-23 01:47:11.200000+00:00	2023-08-23 01:47:11.406000+00:00	0.947368	5	gini	/usr/local/lib/python3 packages

## Load best model (MLflow models)

artifact_uri	start_time	end_time	metrics.accuracy	params.max_depth	params.criterion	tags.mlflow.sour
./mlruns/1/5d63abf908a643ac93724bd076496e19/ar	2023-08-23 01:47:10.328000+00:00	2023-08-23 01:47:10.584000+00:00	0.964912	3	gini	/usr/local/lib/python3 packages
./mlruns/1/d845b4259e634b5cb8485012cc6bc01b/ar	2023-08-23 01:47:10.014000+00:00	2023-08-23 01:47:10.263000+00:00	0.964912	2	gini	/usr/local/lib/python3 packages
./mlruns/1/4746bcfe0a5b4936b3350514515e0536/ar	2023-08-23 01:47:10.639000+00:00	2023-08-23 01:47:10.961000+00:00	0.956140	4	gini	/usr/local/lib/python3 packages
./mlruns/1/09ad160ad4734e68a6044e59228c805a/ar	2023-08-23 01:47:11.931000+00:00	2023-08-23 01:47:12.131000+00:00	0.947368	3	entropy	/usr/local/lib/python3 packages
./mlruns/1/d16fe0518d2d4bff80f343f9a58be6b4/ar	2023-08-23 01:47:11.200000+00:00	2023-08-23 01:47:11.406000+00:00	0.947368	5	gini	/usr/local/lib/python3 packages

```
# Load model as a PyFuncModel.
loaded_model = mlflow.pyfunc.load_model(model_uri=f"runs:/{run_id}/model") # run_id of best model

# Predict on a Pandas DataFrame.
predicted = loaded_model.predict(pd.DataFrame(X_test))
print(classification_report(y_test, predicted, target_names=['Non-DD', 'DD'], digits=4))

Python
```

	precision	recall	f1-score	support
Non-DD DD	0.9778 0.9565	0.9362 0.9851	0.9565 0.9706	47 67
accuracy			0.9649	114
macro avg	0.9671	0.9606	0.9636	114
weighted avg	0.9653	0.9649	0.9648	114

## **Model registry**

The MLflow Model Registry component is a centralized model store, set of APIs, and UI, to collaboratively
manage the full lifecycle of an MLflow Model. It provides model lineage, model versioning, stage transitions (for
example from staging to production), and annotations.

```
#Register best model
mlflow.register_model(model_uri=model_uri, name="breast_cancer")

Python

Successfully registered model 'breast_cancer'.
2023/08/23 14:12:33 INFO mlflow.tracking._model_registry.client: Waiting up to 300 seconds for model version to finish creation. Model name: breast_cancer,
Created version '1' of model 'breast_cancer'.
```

Load model from registered model

```
model_name = "breast_cancer"
  model version = 1
  # Load model as a PyFuncModel.
  loaded model = mlflow.pyfunc.load model(model uri=f"models:/{model name}/{model version}")
  # Predict on a Pandas DataFrame.
  predicted = loaded_model.predict(pd.DataFrame(X_test))
   print(classification_report(y_test, predicted, target_names=['Non-DD', 'DD'], digits=4))
             precision
                         recall f1-score support
     Non-DD
                0.9778
                         0.9362
                                   0.9565
                0.9565
                         0.9851
                                   0.9706
                                                 67
                                                114
   accuracy
                                   0.9649
  macro avg
               0.9671 0.9606
                                   0.9636
weighted avg
               0.9653
                         0.9649
                                   0.9648
```

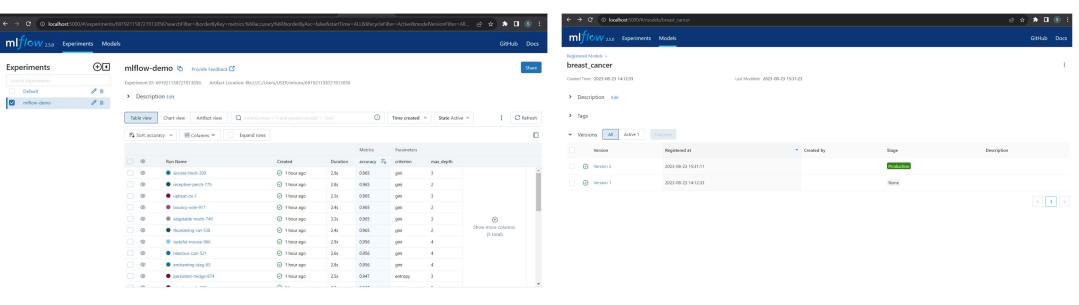
### **MLflow UI**

View MLflow runs and experiments



#### Compare performance

#### Registered model



## For run mlflow ui on google colab

```
# Load and split dataset

X, Y = load_breast_cancer(return_X_y=True)

X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=0)

print("Training Data Shape: ", X_train.shape, y_train.shape)

print("Testing Data Shape: ", X_test.shape, y_test.shape)

local_registry = "sqlite:///mlruns.db"

mlflow.set_tracking_uri(local_registry)

experiment_id = mlflow.set_experiment('test_experiment')

def eval_metrics(actual, pred):
    accuracy = accuracy_score(actual, pred)
    return accuracy
```

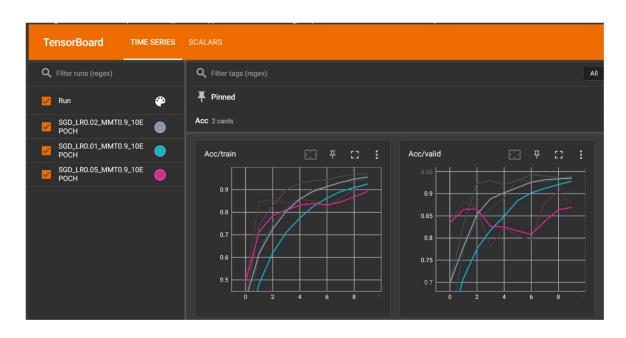
#### Get authtoken from <a href="https://dashboard.ngrok.com/auth">https://dashboard.ngrok.com/auth</a>

## Tensorboard

Guide

#### What is tensorboard

- 1) Visualization toolkit for machine learning training
- 2) Can visualize train/validate loss, accuracy etc.
- 3) Benefits in comparing between runs (adjust hyperparameters)



### Tensorboard steps

```
install
                           pip install -qq tensorboard
2) import summarywriter
        from torch.utils.tensorboard import SummaryWriter
1) create directory to save log files e.g. /content/runs/run1/
   instantiate writer
                           writer = SummaryWriter(log dir="./runs/run1/")
   add scalar
                           writer.add scalar("Name", value, round)
   write on disk
                           writer.flush()
   close
                           writer.close()
   launch tensorboard
        %load ext tensorboard
        %tensorboard --logdir runs
```

### References

- [1] https://www.tensorflow.org/tensorboard
- [2] https://pytorch.org/tutorials/recipes/recipes/tensorboard\_with\_pytorch.html

# WandB

Guide

#### What is WandB

- Special tools by Weights & Biases for
  - experiments tracking
  - results visualization
  - hyperparameter adjustment (sweep)
  - reproduce models
  - o and more!
- Create account <a href="https://wandb.ai/site">https://wandb.ai/site</a>
- Get API key (Need when login) <a href="https://wandb.ai/authorize">https://wandb.ai/authorize</a>

## Steps: Dashboard

```
1) install
              !pip install wandb
2) import
              import wandb
3) login
              wandb.login() # this one is for the imported wandb library
4) initiate
              wandb.init(
                               project="Animal-EfficientNetB0",
                               config={"learning_rate": 0.02,
                                            "architecture": "EfficientNetB0",
                                            "dataset": "Animal2",
                                            "epochs": 10}
5) log
                    wandb.log({"acc": acc, "loss": loss})
6) finish
                    wandb.finish()
```

## Steps: Sweep

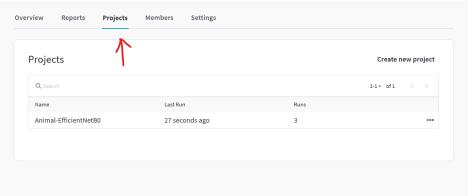
```
1) install
        !pip install wandb
2) import
        import wandb
3) login
        wandb.login()
4) create config (dict)
                                                sweep config = dict()
5) write your own training function
                                                train()
6) write WandB training function on top
                                                trainer()
7) initiate sweep (via wandb agent)
                                                wandb.agent(sweep_id, train)
8) get results at your account page
                                                https://wandb.ai/
```

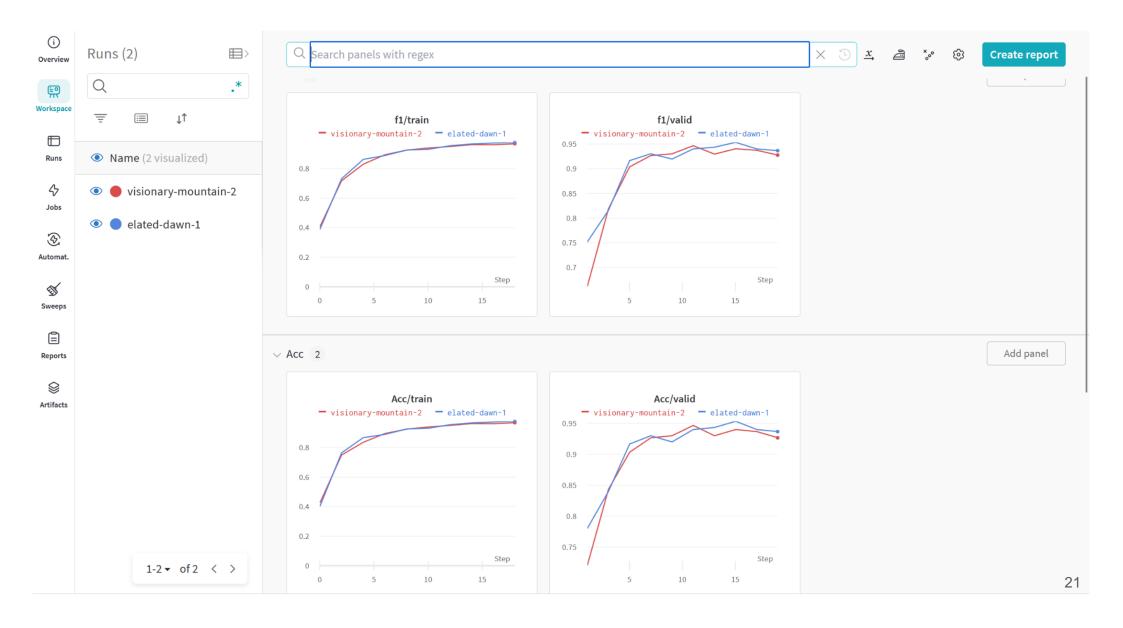
#### Results

Run history and run summary in your notebook



Full dashboard in your wandb profile





## References

[1] https://wandb.ai/home