Platform for Machine Learning Lifecycle

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MLOps: Production & Engineering World

Outline – Introduction to MLflow: How to Use MLflow Tracking - Module 1

- Overview of ML development challenges
- How MLflow tackles these
- Concepts and Motivations
- MLFlow Components
  - MLflow Tracking
  - How to use MLflow Tracking APIs
  - Use Databricks Community Edition
  - Explore MLflow UI
  - Tutorials & Exercises
- Q & A

https://github.com/dmatrix/tmls-workshop

Machine Learning Development is Complex

Traditional Software vs. Machine Learning

Traditional Software

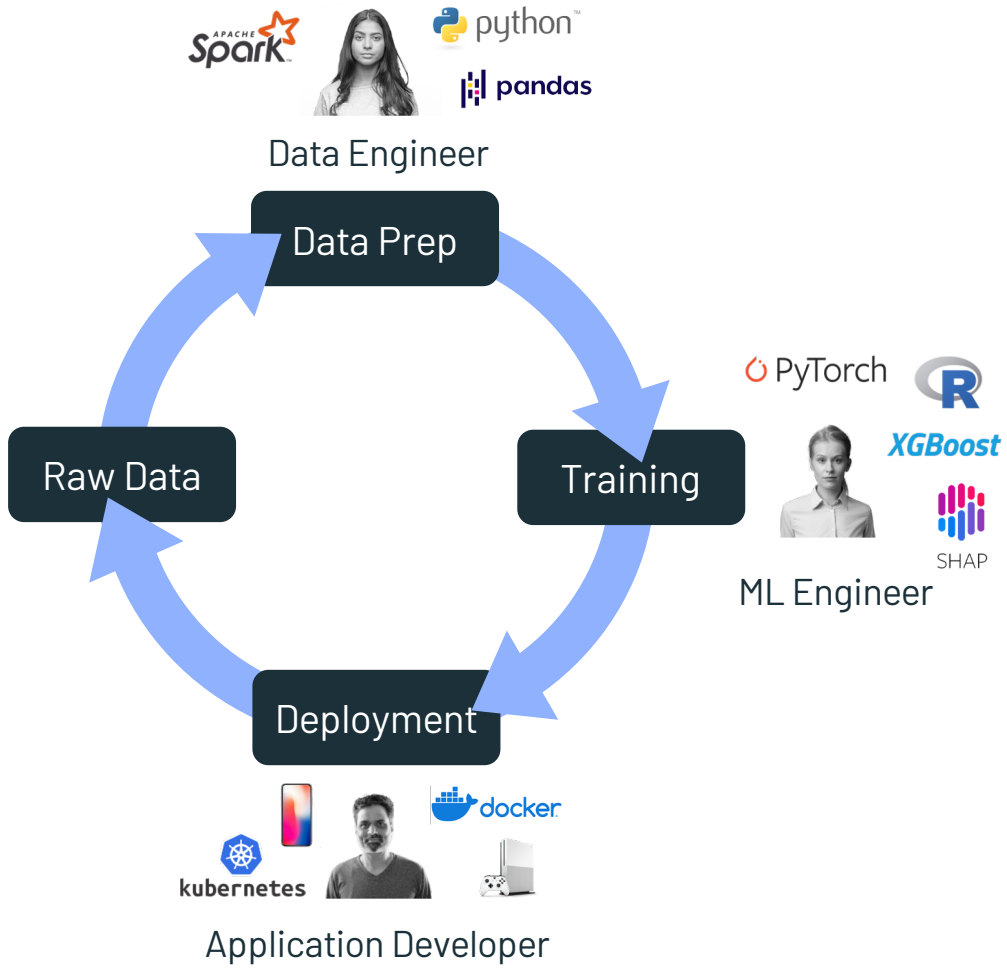
- Goal: Meet a functional specification
- Quality depends only on code
- Typically pick one software stack w/ fewer libraries and tools
- Limited deployment environments

Machine Learning

- Goal: Optimize metric (e.g., accuracy. Constantly experiment to improve it
- Quality depends on input data and tuning parameters
- Over time data changes; models drift…
- Compare + combine many libraries, model
- Diverse deployment environments

But Building ML Applications is Complex

- Continuous, iterative process
- Dependent on data
- Many teams and systems involved



Solution: ML Platforms

Software platforms to manage the ML application lifecycle, from data to experimentation to production

Examples: Google TFX, Facebook FBLearner, Uber Michelangelo

Can we get these benefits with an open source platform?

mlflow: An Open Source ML Platform

mlflow TRACKING

Experiment management

mlflow PROJECTS

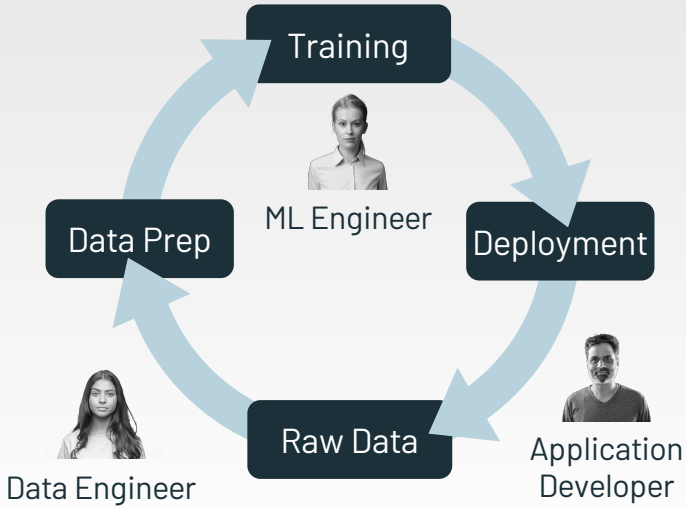
Reproducible runs

mlflow MODELS

Model packaging and deployment

mlflow MODEL REGISTRY

Model management



Any Language

python · R · Java · Scala

Any ML Library

TensorFlow · PyTorch · Keras · Spark · learn · H2O.ai · mleap · ONNX · GLUON · XGBoost · LightGBM · CONDA · kubernetes · docker · Amazon SageMaker · Azure Machine Learning · Google Cloud

Key Concepts in MLflow Tracking

Parameters: key-value inputs to your code

Metrics: numeric values (can update over time)

Tags and Notes: information about a run

Artifacts: files, data, and models

Source: what code ran?

Version: what of the code?

Run: an instance of code that runs by MLflow

Experiment: {Run, ... Run}

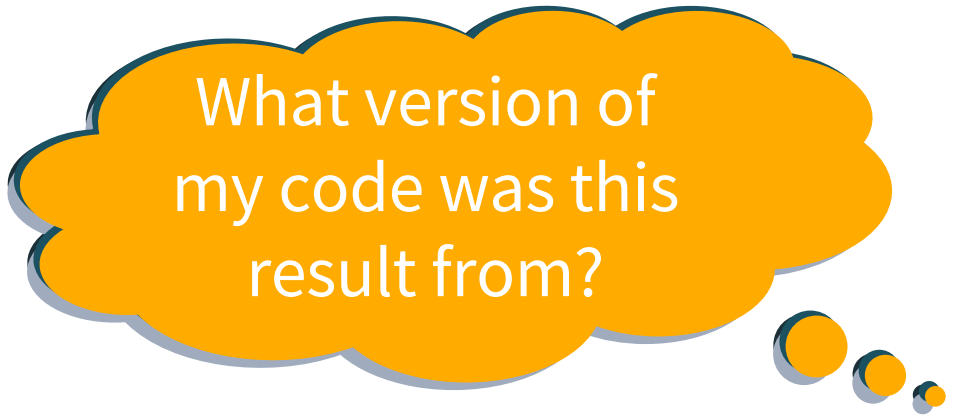
Model Development *without* MLflow Tracking

```
data   = load_text(file_name=file)
ngrams = extract_ngrams(data, N=n)
model  = train_model(ngrams,
                     learning_rate=lr)
score  = compute_accuracy(model)

print("For n=%d, lr=%f: accuracy=%f"
      % (n, lr, score))

pickle.dump(model, open("model.pkl"))
```

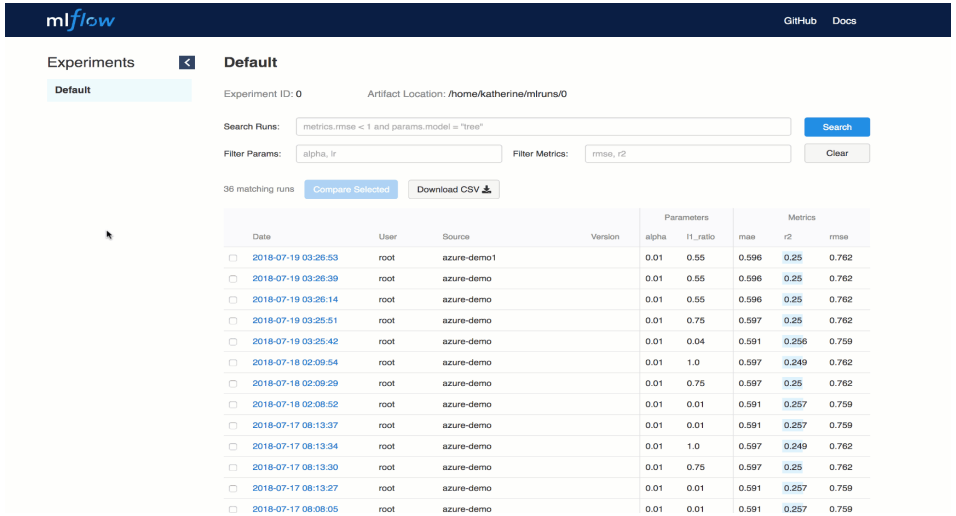
```
For n=2, lr=0.1: accuracy=0.71
For n=2, lr=0.2: accuracy=0.79
For n=2, lr=0.5: accuracy=0.83
For n=2, lr=0.9: accuracy=0.79
For n=3, lr=0.1: accuracy=0.83
For n=3, lr=0.2: accuracy=0.82
For n=4, lr=0.5: accuracy=0.75
...
```



Model Development *with* MLflow is *Simple!*

```
import mlflow
data   = load_text(file_name=file)
ngrams = extract_ngrams(data, N=n)
model  = train_model(ngrams,
                     learning_rate=lr)
score  = compute_accuracy(model)
with mlflow.start_run():
  mlflow.log_param("data_file", file)
  mlflow.log_param("n", n)
  mlflow.log_param("learn_rate", lr)
  mlflow.log_metric("score", score)
  mlflow.sklearn.log_model(model)
```

```
$ mlflow ui
```



Track parameters, metrics, artifacts, output files & code version

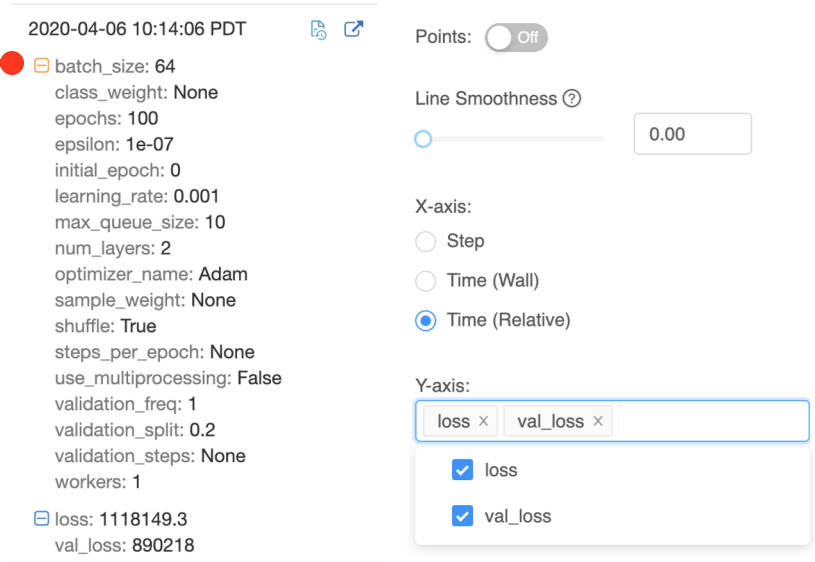
mlflow Tracking for ML Experiments

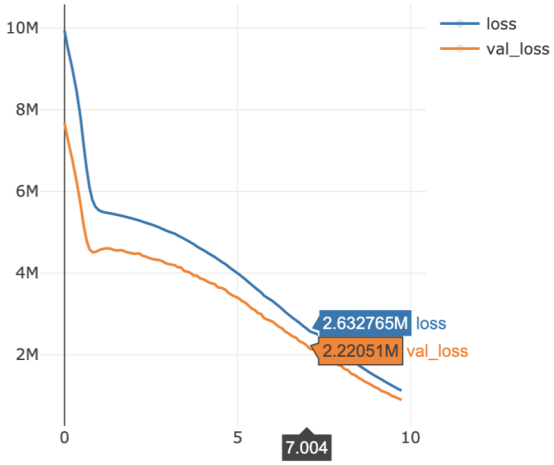
Easily track parameters, metrics, and artifacts in popular ML libraries

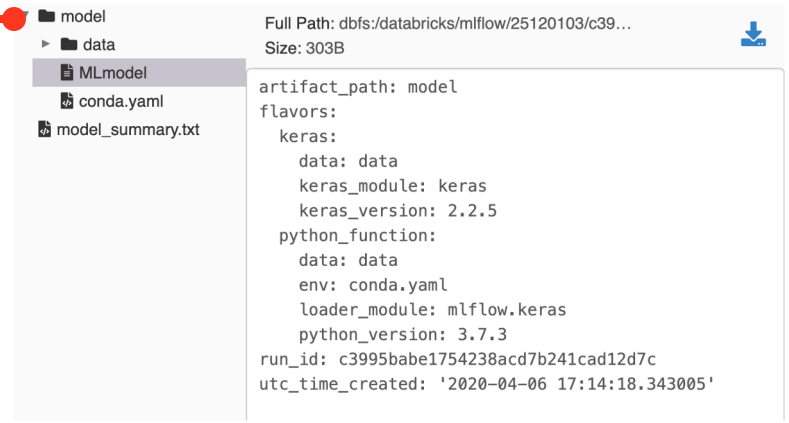
```
with mlflow.start_run(run_name='keras'):
  # log model and datasource
  mlflow.keras.autolog()
```

Library integrations:

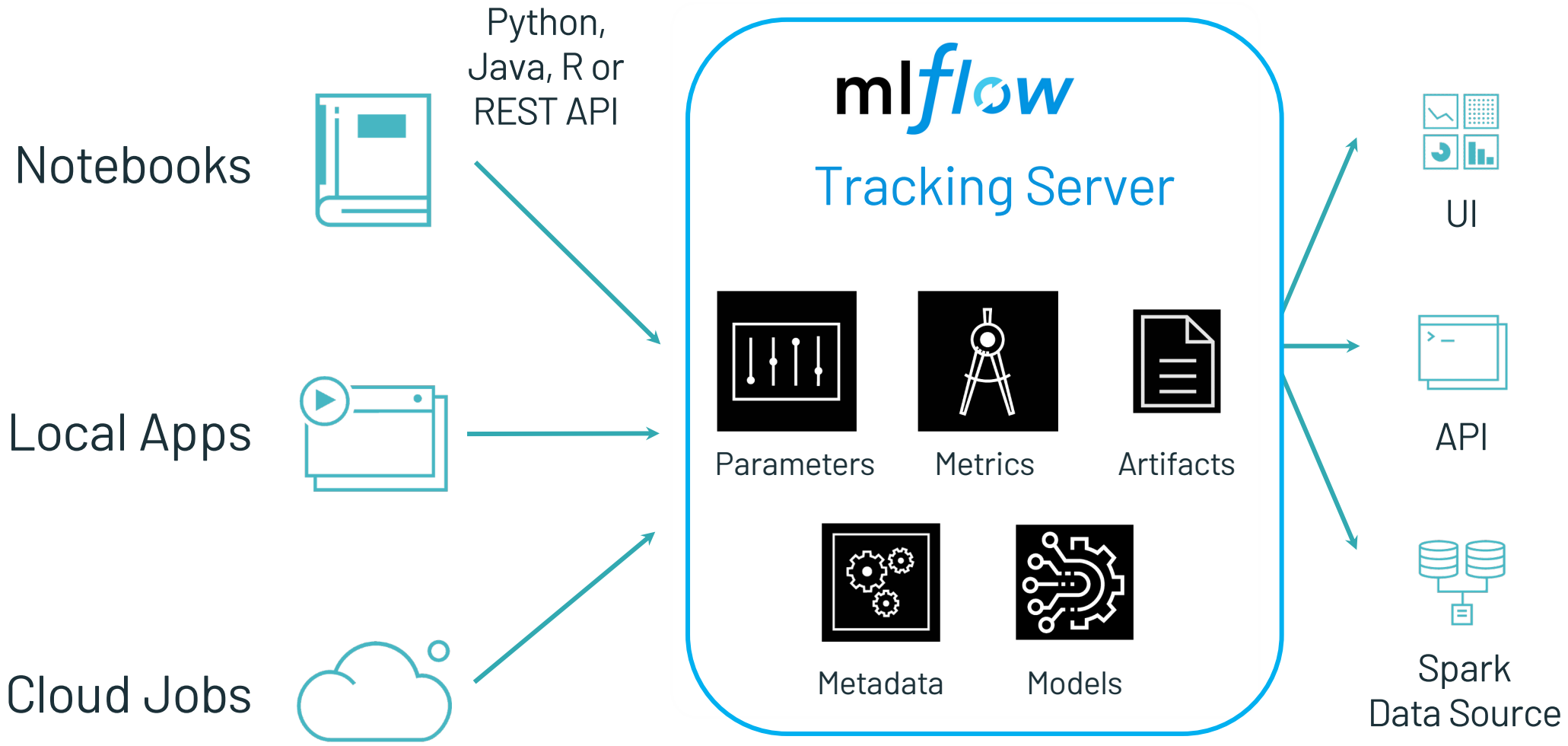
scikit learn · PyTorch · TensorFlow · Keras · Apache Spark · RAPIDS · H2O.ai · GLUON · XGBoost · LightGBM · spaCy · fast.ai · PyCaret · SHAP · Optuna · Delta Lake





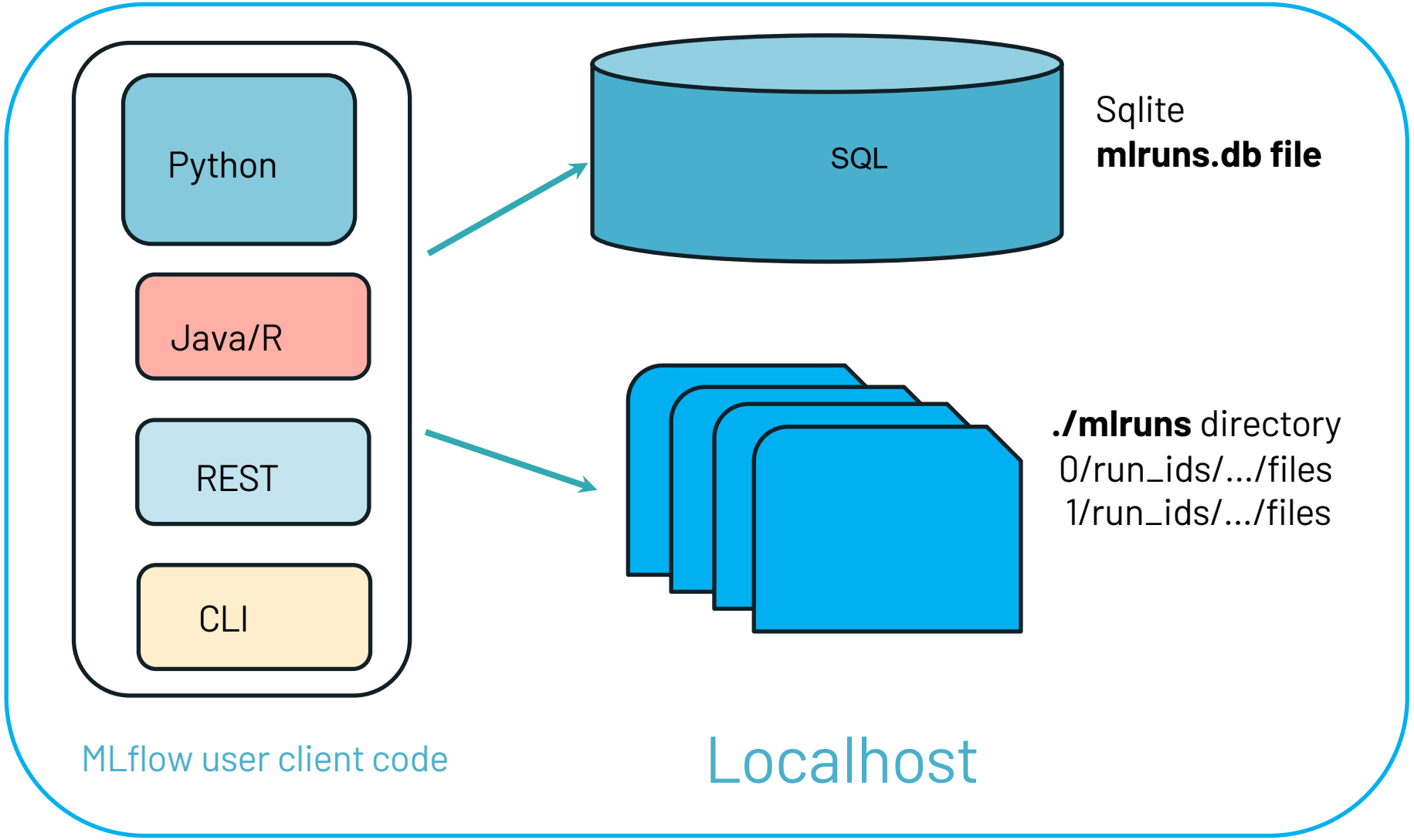


MLflow Tracking Server

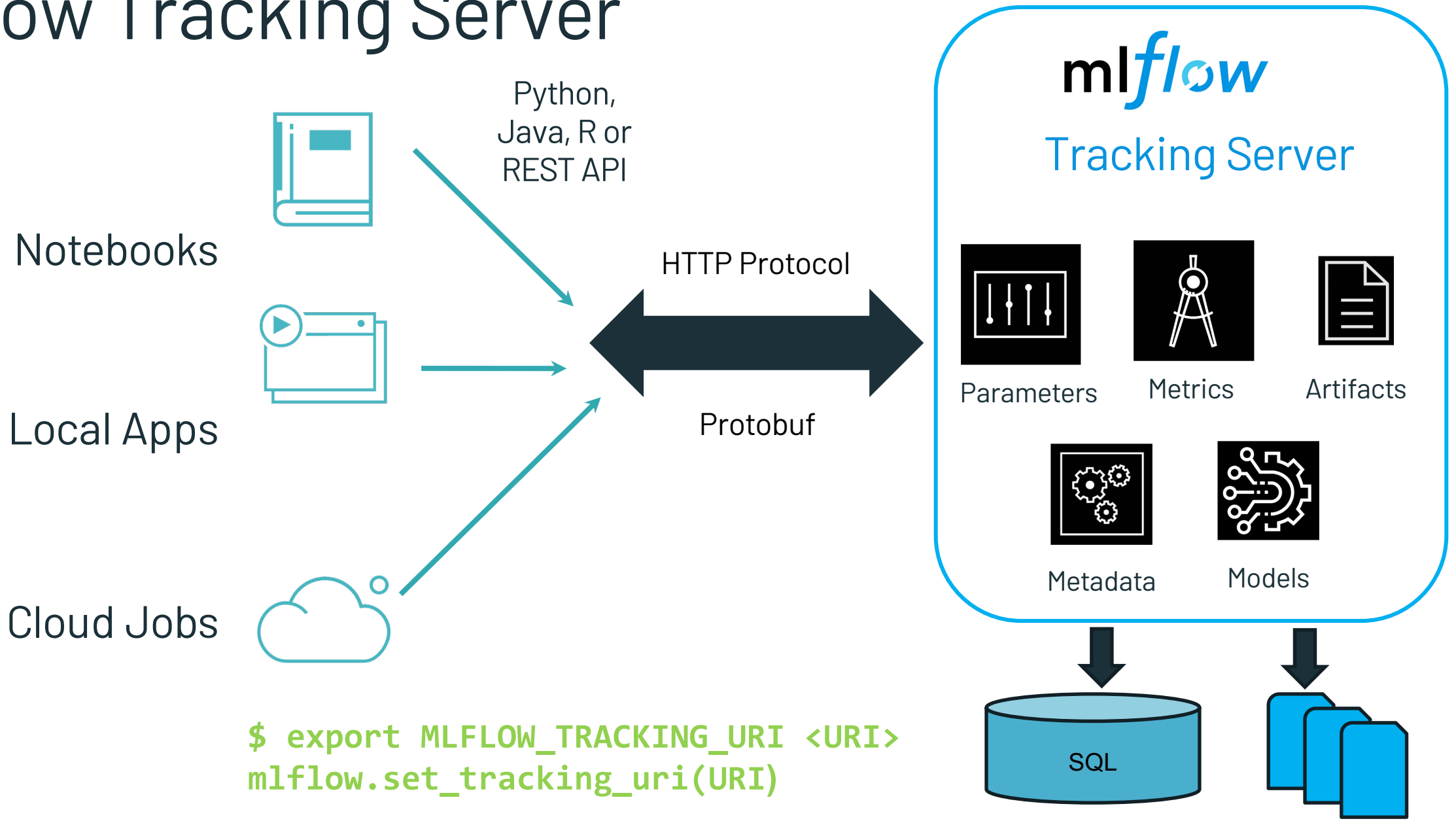



```
$ export MLFLOW_TRACKING_URI <URI>
mlflow.set_tracking_uri(URI)
```

MLflow Tracking Local Storage



MLflow Tracking Server




```
$ export MLFLOW_TRACKING_URI <URI>
mlflow.set_tracking_uri(URI)
```

Python API

The MLflow Python API is organized into the following modules. The most common functions are exposed in the `mlflow` module, so we recommend starting there.

- mlflow
- mlflow.azureml
- mlflow.deployments
- mlflow.entities
- mlflow.fastai
- mlflow.gluon
- mlflow.h2o
- mlflow.keras
- mlflow.lightgbm
- mlflow.mleap
- mlflow.models
- mlflow.onnx
- mlflow.projects
- mlflow.pyfunc
  - Inference API
  - Filesystem format
    - MLModel configuration
  - Creating custom Pyfunc models
    - Workflows
    - Which workflow is right for my use case?
- mlflow.pytorch
- mlflow.sagemaker
- mlflow.sklearn
- mlflow.spacy
- mlflow.spark
- mlflow.tensorflow
- mlflow.tracking

MLflow API Data Flow: Localhost defaults

- **No** mlflow server --backend-store-uri --default-root-artifact-uri
- **No** REST calls to the Tracking Service
- **Everything** stored under local directory **mlruns**

```
with mlflow.start_run(run_name="DEFAULTS") as run:
    params = {"n_estimators": 3, "random_state": 42}
    sk_learn_rfr = RandomForestRegressor(params)

    # Log params using the MLflow sklearn APIs
     mlflow.log_params(params)
    mlflow.log_param("param_1", randint(0, 100))
    mlflow.log_metric("metric_1", random())
    mlflow.log_metric("metric_2", random() + 1)
    mlflow.sklearn.log_model(sk_learn_rfr,
                             artifact_path="sklearn-model")
```

```
mlruns
└── 0
    ├── e7d505e713f14d64a74279f6c1a5d8e7
    │   ├── artifacts
    │   │   └── sklearn-model
    │   │       ├── MLmodel
    │   │       ├── conda.yaml
    │   │       └── model.pkl
    │   ├── meta.yaml
    │   ├── metrics
    │   │   ├── metric_1
    │   │   └── metric_2
    │   ├── params
    │   │   ├── n_estimators
    │   │   ├── param_1
    │   │   └── random_state
    │   └── tags
    │       ├── mlflow.log-model.history
    │       ├── mlflow.runName
    │       ├── mlflow.source.git.commit
    │       ├── mlflow.source.name
    │       ├── mlflow.source.type
    │       └── mlflow.user
    └── meta.yaml

7 directories, 16 files
```

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MLflow API Data Flow: Localhost w/ SQLAlchemy backend store

- **No** mlflow server --backend-store-uri --default-root-artifact-uri
- **No** REST calls to the Tracking Service
- **Artifacts** stored under local directory **mlruns**
- **Mlflow** entities stored in **mlruns.db**

```
local_store_uri = "sqlite:///mlruns.db"
mlflow.set_tracking_uri(local_store_uri)
```

```
with mlflow.start_run(run_name="LOCAL_REGISTRY") as run:
    params = {"n_estimators": 3, "random_state": 42}
    sk_learn_rfr = RandomForestRegressor(params)

    # Log params using the MLflow sklearn APIs
    mlflow.log_params(params)
    mlflow.log_param("param_1", randint(0, 100))
    mlflow.log_metric("metric_1", random())
    mlflow.log_metric("metric_2", random() + 1)
    mlflow.sklearn.log_model(sk_learn_rfr,
          artifact_path="sklearn-model")
```

```
mlruns
└── 0
    └── 1f896ddc61d34d089d4126eddceb5b52
        └── artifacts
            └── sklearn-model
                ├── MLmodel
                ├── conda.yaml
                └── model.pkl

4 directories, 3 files
```

```
(tutorials) ➜  mlflow_fluent git:(master) ✗ sqlite3 mlruns.db
SQLite version 3.30.1 2019-10-10 20:19:45
Enter ".help" for usage hints.
sqlite> .tables
alembic_version        metrics                registered_model_tags
experiment_tags        model_version_tags     registered_models
experiments            model_versions         runs
latest_metrics         params                 tags
sqlite> select * from params;
n_estimators|3|29c1e723cfad48bbbc20c4ca52414780
random_state|42|29c1e723cfad48bbbc20c4ca52414780
param_1|10|29c1e723cfad48bbbc20c4ca52414780
sqlite> select * from metrics;
metric_1|0.216184107170305|1597259612673|29c1e723cfad48bbbc20c4ca52414780|0|0
metric_2|1.17106399018329|1597259612697|29c1e723cfad48bbbc20c4ca52414780|0|0
sqlite>
```

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MLflow API Data Flow: Use Tracking Server SQLAlchemy backend store

```
mlflow server --backend-store-uri sqlite:///mnt/backend-end/mlruns.db \
              --default-artifact-root s3://my-mlflow-bucket  \
              --host host.mydomain.com
```

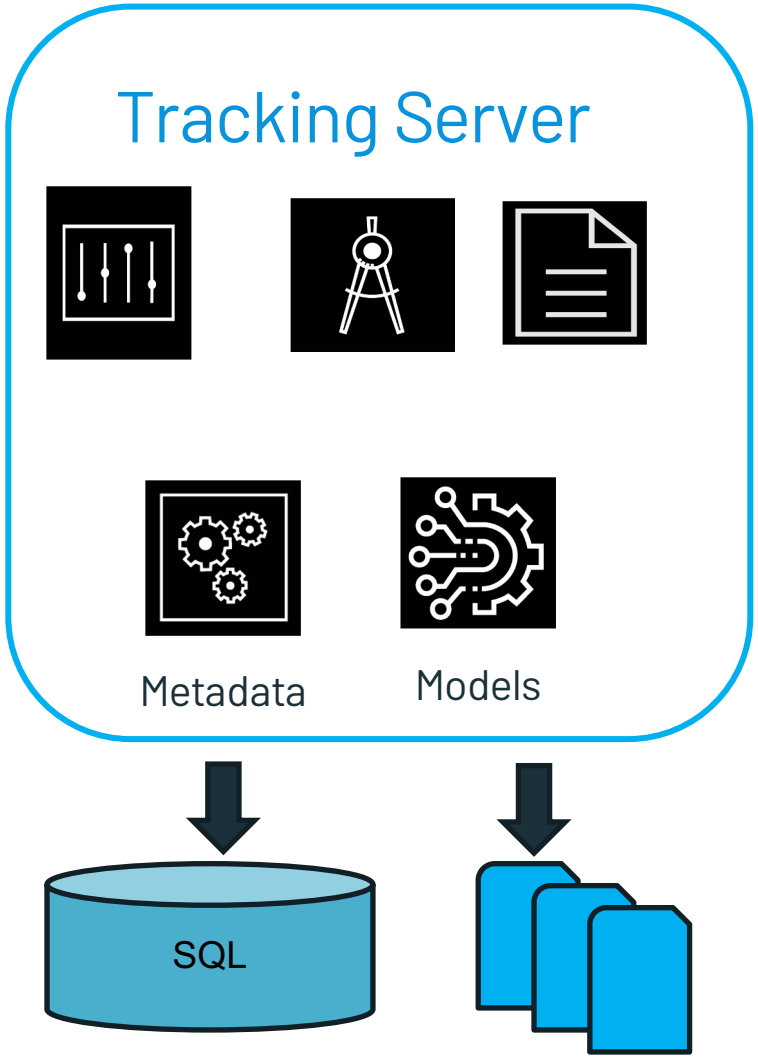
```
tracking_uri = “https://host.mydomain.com:5000”
mlflow.set_tracking_uri(tracking_uri)
```

```
with mlflow.start_run(run_name="LOCAL_REGISTRY") as run:
    params = {"n_estimators": 3, "random_state": 42}
    sk_learn_rfr = RandomForestRegressor(params)

    # Log params using the MLflow sklearn APIs
    mlflow.log_params(params)
    mlflow.log_param("param_1", randint(0, 100))
    mlflow.log_metric("metric_1", random())
    mlflow.log_metric("metric_2", random() + 1)
    mlflow.sklearn.log_model(sk_learn_rfr,
          artifact_path="sklearn-model")
```

HTTP Protocol

REST API



Backend Store URI Format: MySQL, PostgreSQL, SQLite, etc.

```
<dialect>+<driver>://<username>:<password>@<host>:<port>/<database>
```

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MLflow set of APIs

Fluent MLflow APIs

- Python
  - High-level operations for runs and experiments
  - Model Flavor APIs
- Java
  - MLflowContext
  - Experiments, runs, search, etc
- R
  - Experiments, runs, search etc

MLflowClient

- Low Level CRUD interface to experiments, runs, Entities, Model Registry, etc
- `import mflow.tracking`
- `client = MLflowClient(**kwargs)`
- `Metric,Param,Search etc`

MLflow REST API

- Make REST calls to Tracking server with endpoints
- `https://<traciking_server>/api/..`
- `/2.0/mlfow/2.0/runs/log-metric`
- `/2.0/mlflow/runs/log-parameter`
- `/2.0/mlflow/runs/search`

mlflow Tracking for Model Schemas

Record what fields are consumed & produced by the model to prevent data mismatches

in MLflow 1.11

```
with mlflow.start_run(run_name='keras'):
  # log model and datasource
  mlflow.keras.autolog()
  mlflow.spark.autolog()

  sig = infer_signature(X_train, y_train)
```

▾ Schema

Name	Type
Inputs (7)	
user_purchases_7d	long
user_purchases_14d	long
user_location	string
user_last_login	string
item_inventory	long
Outputs (1)	
prediction	double

mlflow Tracking for Interpretability

SHAP library feature importances and visualizations

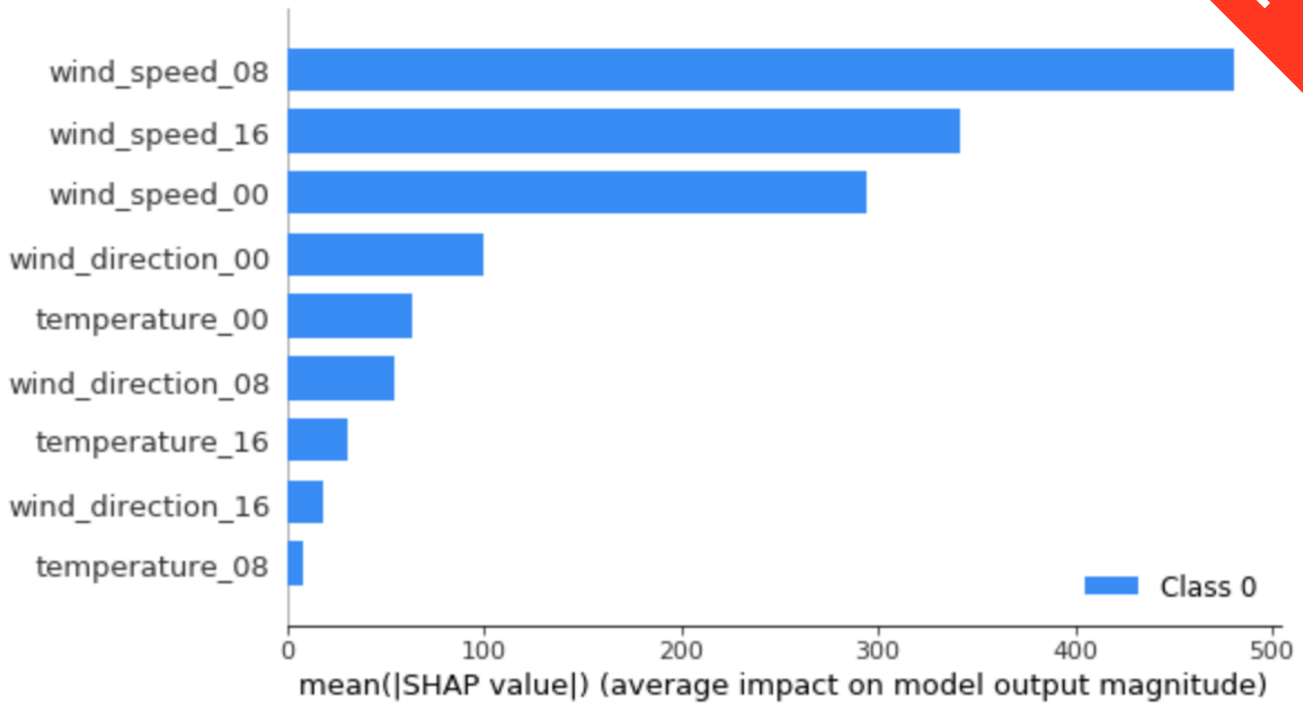
in MLflow 1.12

```
with mlflow.start_run(run_name='keras'):
  # log model and datasource
  mlflow.keras.autolog()
  mlflow.spark.autolog()

  sig = infer_signature(X_train, y_train)

  mlflow.shap.log_explanation(model, X_train[:100])
```

SHAP



Easily log and query all aspects of your ML development process

mlflow + PyTorch

in MLflow 1.12

Collaboration between Facebook and Databricks to bring ML platform features to PyTorch

- MLflow autologging for PyTorch Lightning
- TorchScript support for faster packaged models
- Model deployment to TorchServe

MLflow 1.12 Features Extended PyTorch Integration

And model explainability, autologging, and other enhancements

by Jules Damji, Siddharth Murching and Harutaka Kawamura
Posted in **ENGINEERING BLOG** | November 13, 2020

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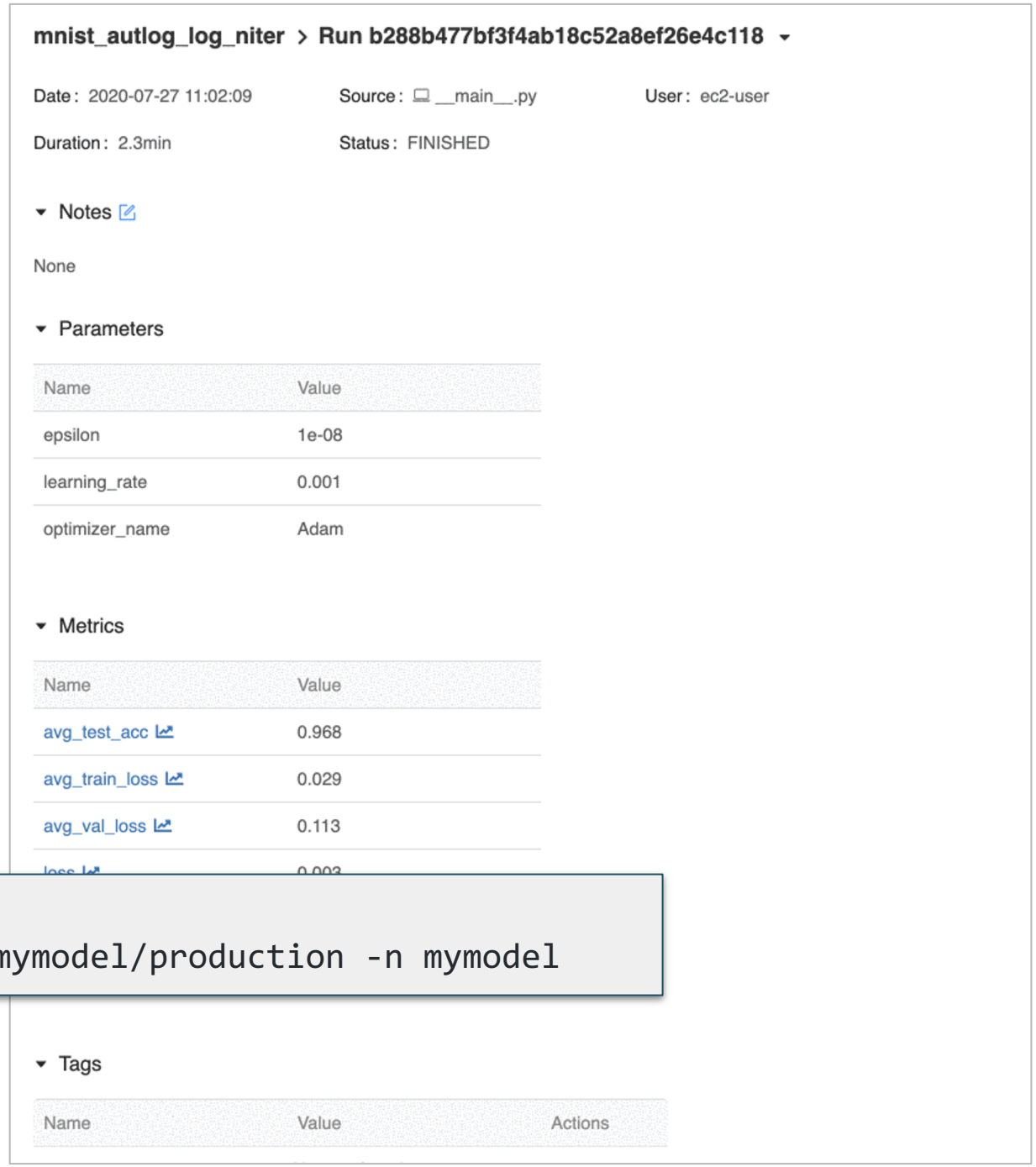
mlflow + PyTorch

```
# Enable MLflow autologging
import mlflow.pytorch_lightning
mlflow.pytorch_lightning.autolog()

# Train a model with PyTorch Lightning
model = MyModel()
trainer = pl.Trainer()
trainer.fit(model, train, val)
```

```
# Deploy to TorchServe
mlflow deployments create -t torchserve -m models:/mymodel/production -n mymodel
```



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What Did We Talk About? mlflow™

- Modular Components greatly simplify the ML lifecycle
- Easy to install and use & Great Developer Experience
- Develop & Deploy locally and track locally or remotely
- Available APIs: Python, Java & R (Soon Scala)
- Visualize experiments and compare runs

Learning More About MLflow & Get Involved!

- pip install mlflow – to get started
- Find docs & examples at mlflow.org
- Peruse code and contribute at MLflow Github
- Join the Slack channel
- More MLflow tutorials

Thank you! ☺

Q & A

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