

mlflow

Platform for Machine Learning Lifecycle

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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/olt-mlflow>

Machine Learning Development is Complex

Traditional Software vs. Machine Learning

Traditional Software

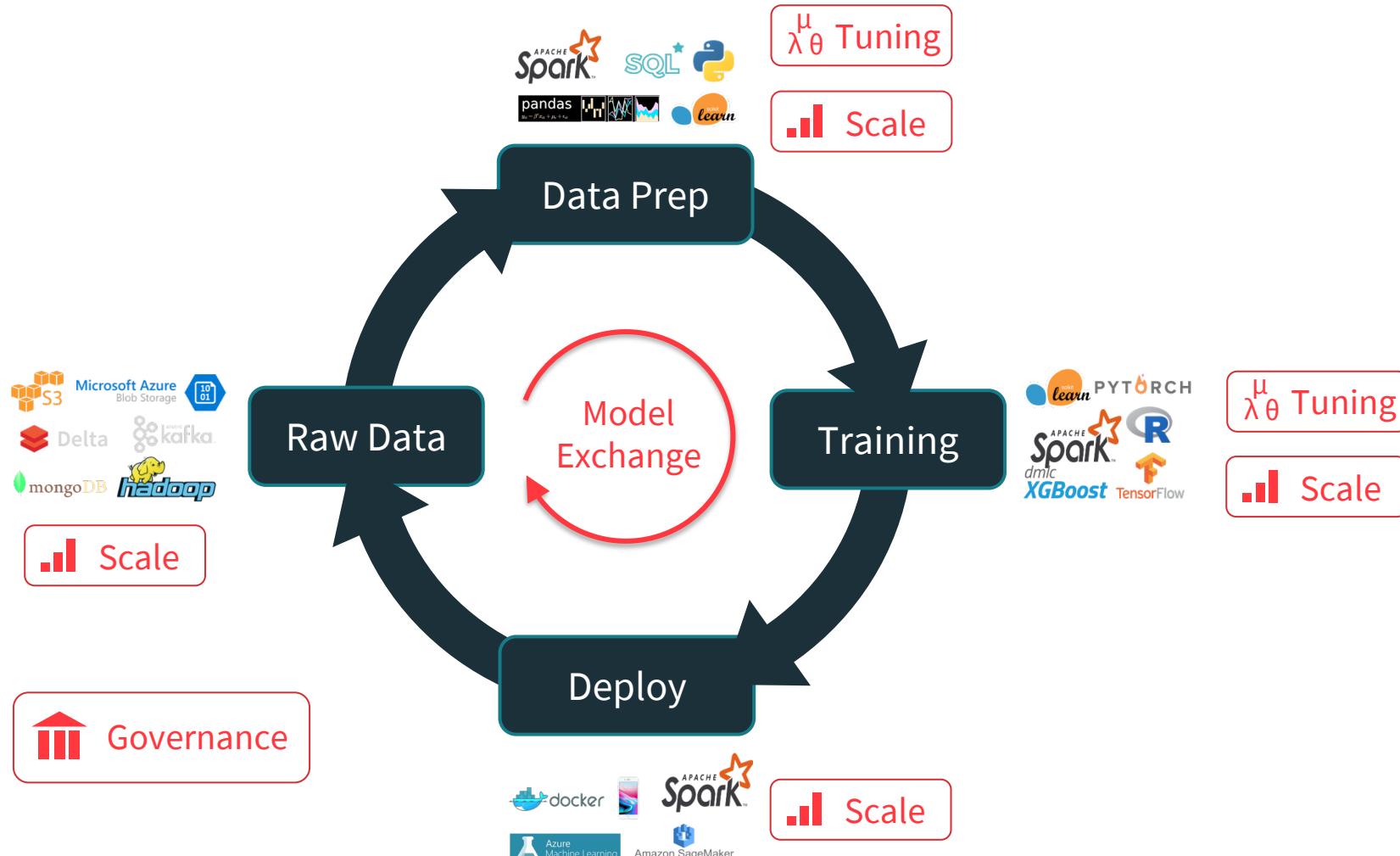
- **Goal:** Meet a functional specification
- Quality depends only on code
- Typically pick one software stack w/ fewer libraries and tools
- Limited deployment environments

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



Machine Learning Lifecycle



Custom Machine Learning Platforms

Some Big Data Companies

- + Standardize the data prep / training / deploy loop:
if you work with the platform, you get these!
- Limited to a few algorithms or frameworks
- Tied to one company's infrastructure
- Out of luck if you left the company....

Can we provide similar benefits in an **open** manner?

Introducing **mlflow**

Open machine learning platform

Works with popular ML library & language

Runs the same way anywhere (e.g., any cloud or locally)

Designed to be useful for 1 or 1000+ person orgs

Simple. Modular. Easy-to-use.

Offers positive developer experience to get started!

MLflow Design Philosophy

API-First

- Submit runs, log models, metrics, etc. from popular library & language
- Abstract “model” lambda function that MLflow can then deploy in many places (Docker, Azure ML, Spark UDF)
- Open interface allows easy integration from the community

**Key enabler: built around
Programmatic APIs, REST APIs & CLI**

Modular Design

- Allow different components individually (e.g., use MLflow’s project format but not its deployment tools)
- Not monolithic
- But Distinctive and Selective

**Key enabler: distinct components
(Tracking/Projects/Models/Registry)**

MLflow Components

mlflow

Tracking

Record and query experiments: code, data, config, and results

mlflow

Projects

Package data science code in a format that enables reproducible runs on many platform

mlflow

Models

Deploy machine learning models in diverse serving environments

new

mlflow

Model Registry

Store, annotate and manage models in a central repository

[databricks.com
/mlflow](https://databricks.com/mlflow)



mlflow.org



github.com/mlflow



twitter.com/MLflow

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mlflow: An Open Source ML Platform

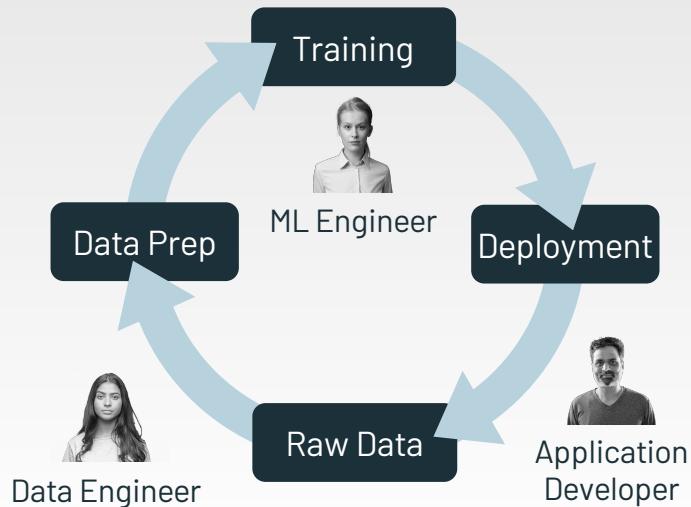
mlflow
TRACKING
Experiment management

mlflow
PROJECTS
Reproducible runs

mlflow
MODELS
Model packaging and deployment

mlflow
MODEL REGISTRY
Model management

Any Language



Any ML Library



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"))
```

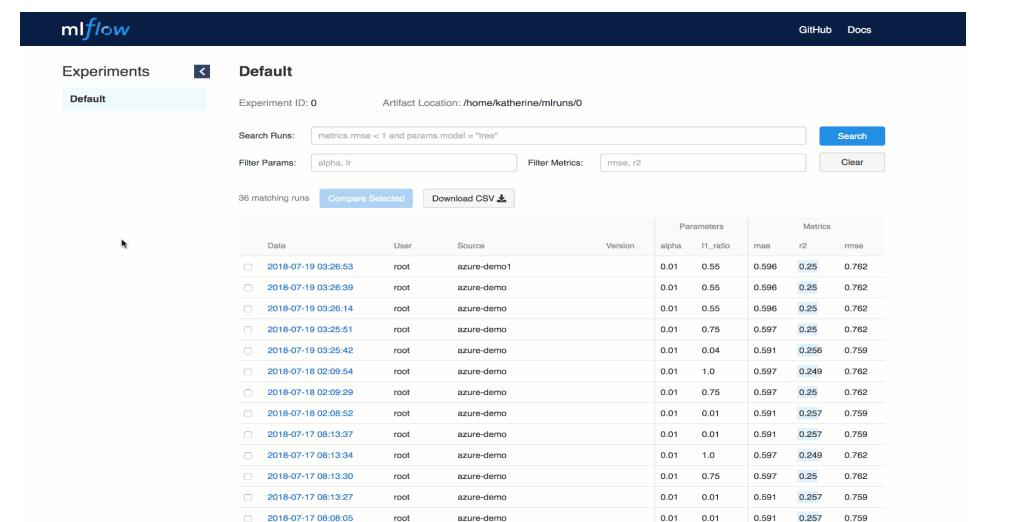
```
For n=2, lr=0.1: accuracy=0.71
For n=2, lr=0.2: accuracy=0.79
For n=2, lr=0.5: accuracy=0.83
For n=2, lr=0.9: accuracy=0.79
For n=3, lr=0.1: accuracy=0.83
For n=3, lr=0.2: accuracy=0.82
For n=4, lr=0.5: accuracy=0.75
...
```

What version of
my code was this
result from?

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



The screenshot shows the MLflow UI interface. At the top, there's a search bar with the query "metrics.rmse < 1 and params.model = 'tree'". Below the search bar, there are sections for "Experiment ID: 0" and "Artifact Location: /home/katherine/mlruns/0". A table below lists 36 matching runs, each with columns for Date, User, Source, Version, Parameters (alpha, H1_ratio), and Metrics (rmse, r2). The table shows multiple runs with different parameter values and metric scores.

Date	User	Source	Version	Parameters	Metrics
2018-07-19 03:26:53	root	azure-demo1	0.01	0.55 0.596 0.25	0.596 0.25 0.762
2018-07-19 03:26:39	root	azure-demo	0.01	0.55 0.596 0.25	0.596 0.25 0.762
2018-07-19 03:26:14	root	azure-demo	0.01	0.55 0.596 0.25	0.596 0.25 0.762
2018-07-19 03:25:51	root	azure-demo	0.01	0.75 0.597 0.25	0.597 0.25 0.762
2018-07-19 03:25:42	root	azure-demo	0.01	0.04 0.591 0.256	0.591 0.256 0.759
2018-07-18 02:09:54	root	azure-demo	0.01	1.0 0.597 0.249	0.597 0.249 0.762
2018-07-18 02:09:29	root	azure-demo	0.01	0.75 0.597 0.25	0.597 0.25 0.762
2018-07-18 02:08:52	root	azure-demo	0.01	0.01 0.591 0.257	0.591 0.257 0.759
2018-07-17 08:13:37	root	azure-demo	0.01	0.01 0.591 0.257	0.591 0.257 0.759
2018-07-17 08:13:34	root	azure-demo	0.01	1.0 0.597 0.249	0.597 0.249 0.762
2018-07-17 08:13:30	root	azure-demo	0.01	0.75 0.597 0.25	0.597 0.25 0.762
2018-07-17 08:13:27	root	azure-demo	0.01	0.01 0.591 0.257	0.591 0.257 0.759
2018-07-17 08:08:05	root	azure-demo	0.01	0.01 0.591 0.257	0.591 0.257 0.759

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

Model Development with MLflow is Simple!

mlflow.<flavor>.autolog() APIs

```
import mlflow
import mlflow.keras

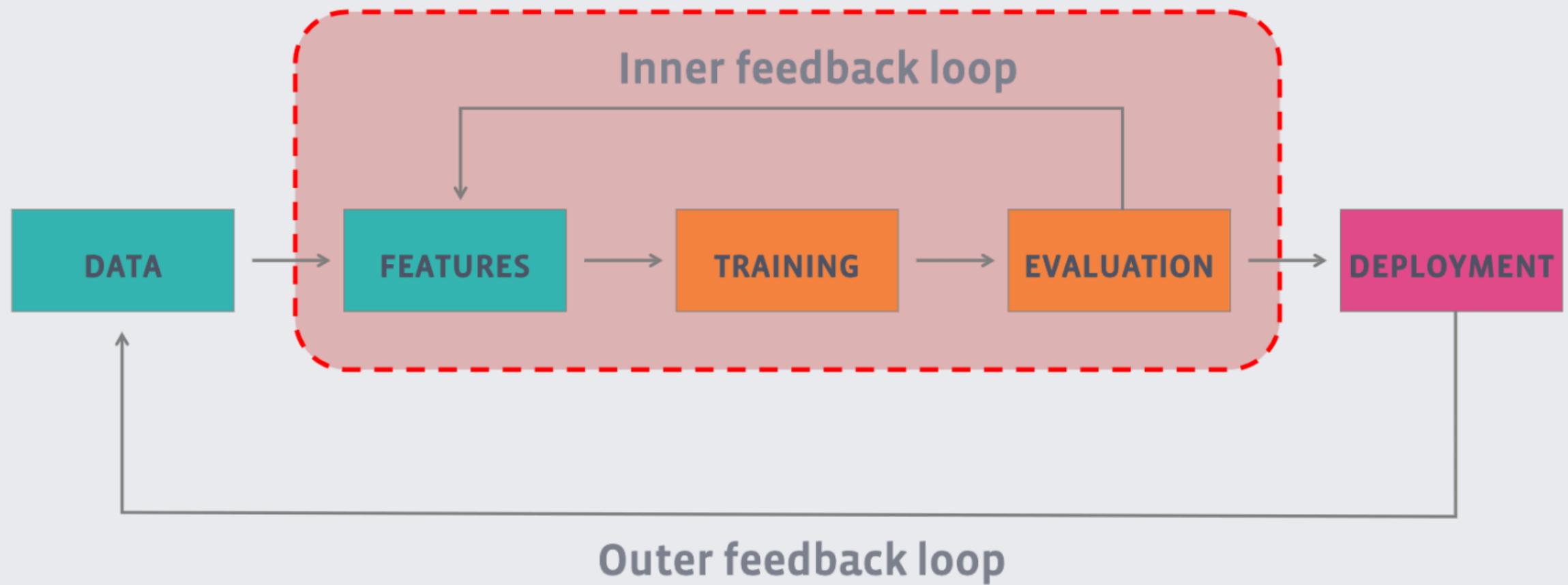
# Build, compile, enable autologging, and
# train your model
keras_model = ...
keras_model.compile(optimizer="rmsprop",
                     loss="mse",
                     metrics=["accuracy"])
# autolog your metrics, parameters, and
# model
mlflow.keras.autolog()
results = keras_model.fit( x_train, y_train,
                           epochs=20, batch_size=128,
                           validation_data=(x_val, y_val))
```

\$ mlflow ui

Date	User	Source	Version	Parameters	Metrics
2018-07-19 03:26:53	root	azure-demo1	0.01	0.55	0.596 0.25 0.762
2018-07-19 03:26:39	root	azure-demo	0.01	0.55	0.596 0.25 0.762
2018-07-19 03:26:14	root	azure-demo	0.01	0.55	0.596 0.25 0.762
2018-07-19 03:25:51	root	azure-demo	0.01	0.75	0.597 0.25 0.762
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2018-07-18 02:09:54	root	azure-demo	0.01	1.0	0.597 0.249 0.762
2018-07-18 02:09:29	root	azure-demo	0.01	0.75	0.597 0.25 0.762
2018-07-18 02:08:52	root	azure-demo	0.01	0.01	0.591 0.257 0.759
2018-07-17 08:13:37	root	azure-demo	0.01	0.01	0.591 0.257 0.759
2018-07-17 08:13:34	root	azure-demo	0.01	1.0	0.597 0.249 0.762
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2018-07-17 08:08:05	root	azure-demo	0.01	0.01	0.591 0.257 0.759

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

Experiment tracking



source: <https://github.com/alfozan/MLflow-GBRT-demo/blob/master/MLflow%20presentation.pdf>

Model Development with MLflow is Simple!

mlflow.<flavor>.autolog() APIs

mlflow Auto-Logging

Currently supported libraries:



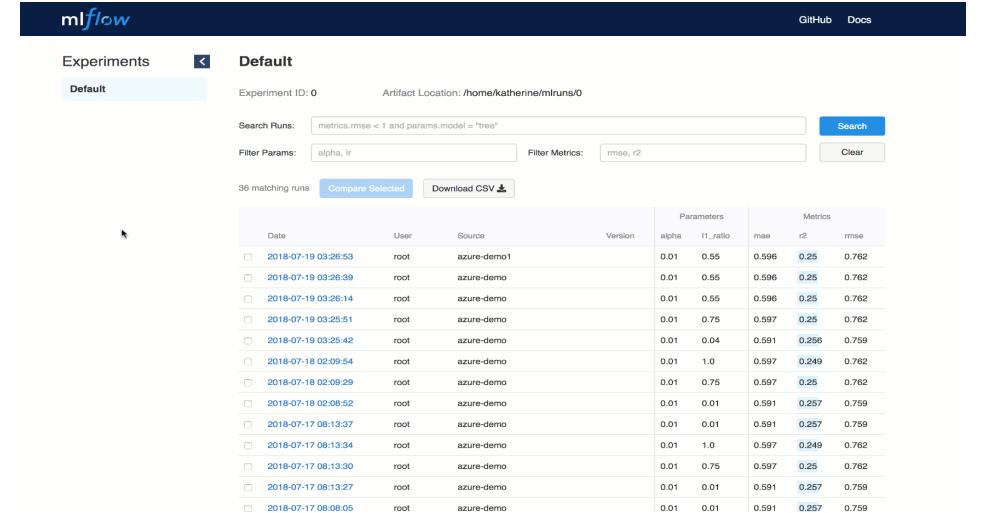
LightGBM



Coming soon:



```
$ mlflow ui
```



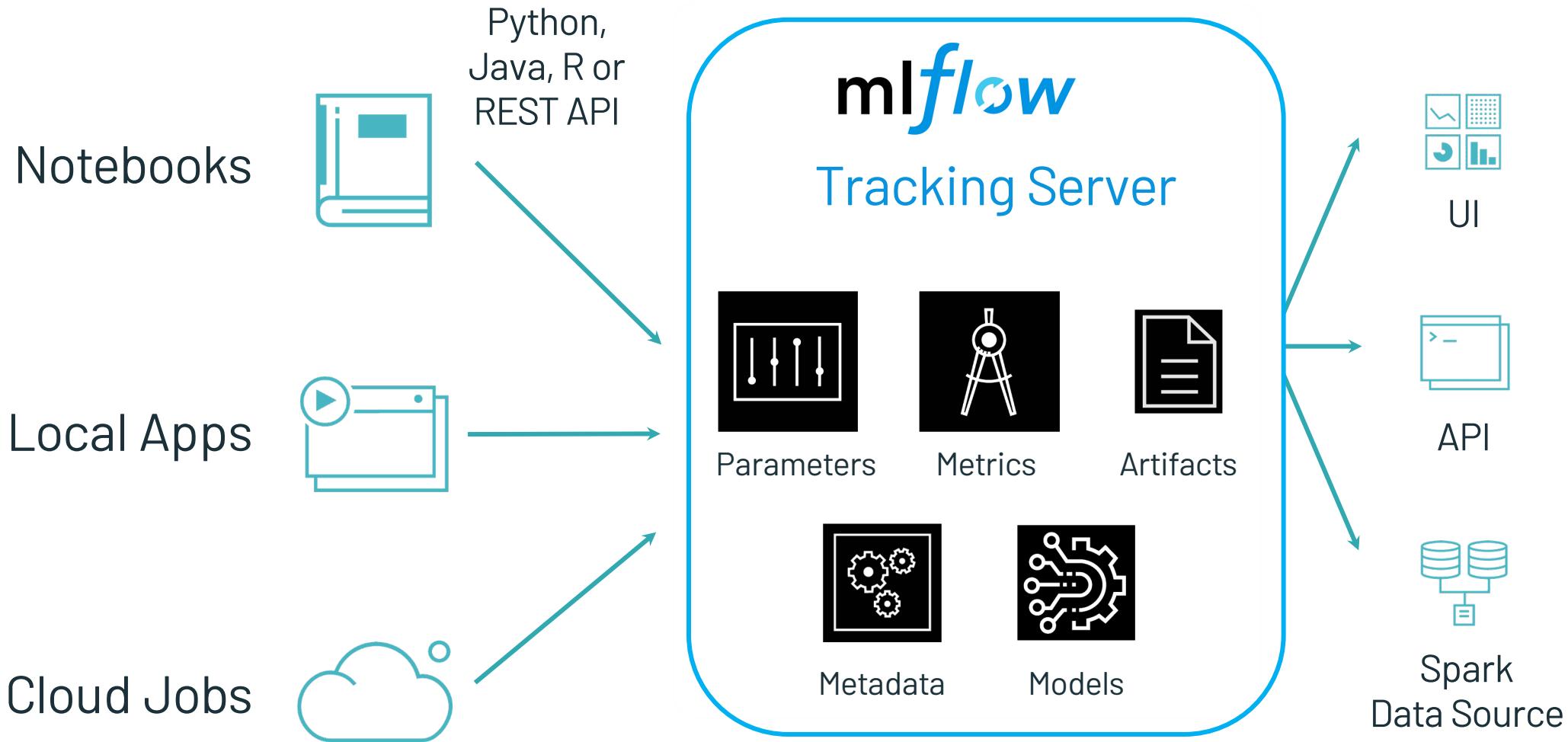
A screenshot of the MLflow UI interface. At the top, there's a dark header with the text '\$ mlflow ui'. Below it is a search bar with the placeholder 'Experiment ID: 0' and 'Artifact Location: /home/katherine/mlruns/0'. Underneath the search bar is a table titled 'Experiments' with a 'Default' tab selected. The table has columns for Date, User, Source, Version, Parameters, and Metrics. It lists 36 matching runs. The parameters column shows values like alpha (0.01), I1_ratio (0.55), rmse (0.596), r2 (0.25), and rmse (0.762). The metrics column shows values like rmse (0.596), r2 (0.25), and rmse (0.762).

Date	User	Source	Version	Parameters	Metrics
2018-07-19 03:26:53	root	azure-demo1		alpha: 0.01, I1_ratio: 0.55	rmse: 0.596, r2: 0.25, rmse: 0.762
2018-07-19 03:26:39	root	azure-demo		alpha: 0.01, I1_ratio: 0.55	rmse: 0.596, r2: 0.25, rmse: 0.762
2018-07-19 03:26:14	root	azure-demo		alpha: 0.01, I1_ratio: 0.55	rmse: 0.596, r2: 0.25, rmse: 0.762
2018-07-19 03:25:51	root	azure-demo		alpha: 0.01, I1_ratio: 0.75	rmse: 0.597, r2: 0.25, rmse: 0.762
2018-07-19 03:25:42	root	azure-demo		alpha: 0.01, I1_ratio: 0.04	rmse: 0.591, r2: 0.256, rmse: 0.759
2018-07-18 02:09:54	root	azure-demo		alpha: 0.01, I1_ratio: 1.0	rmse: 0.597, r2: 0.249, rmse: 0.762
2018-07-18 02:09:29	root	azure-demo		alpha: 0.01, I1_ratio: 0.75	rmse: 0.597, r2: 0.25, rmse: 0.762
2018-07-18 02:08:52	root	azure-demo		alpha: 0.01, I1_ratio: 0.01	rmse: 0.591, r2: 0.257, rmse: 0.759
2018-07-17 08:13:37	root	azure-demo		alpha: 0.01, I1_ratio: 0.01	rmse: 0.591, r2: 0.257, rmse: 0.759
2018-07-17 08:13:34	root	azure-demo		alpha: 0.01, I1_ratio: 1.0	rmse: 0.597, r2: 0.249, rmse: 0.762
2018-07-17 08:13:30	root	azure-demo		alpha: 0.01, I1_ratio: 0.75	rmse: 0.597, r2: 0.25, rmse: 0.762
2018-07-17 08:13:27	root	azure-demo		alpha: 0.01, I1_ratio: 0.01	rmse: 0.591, r2: 0.257, rmse: 0.759
2018-07-17 08:08:05	root	azure-demo		alpha: 0.01, I1_ratio: 0.01	rmse: 0.591, r2: 0.257, rmse: 0.759

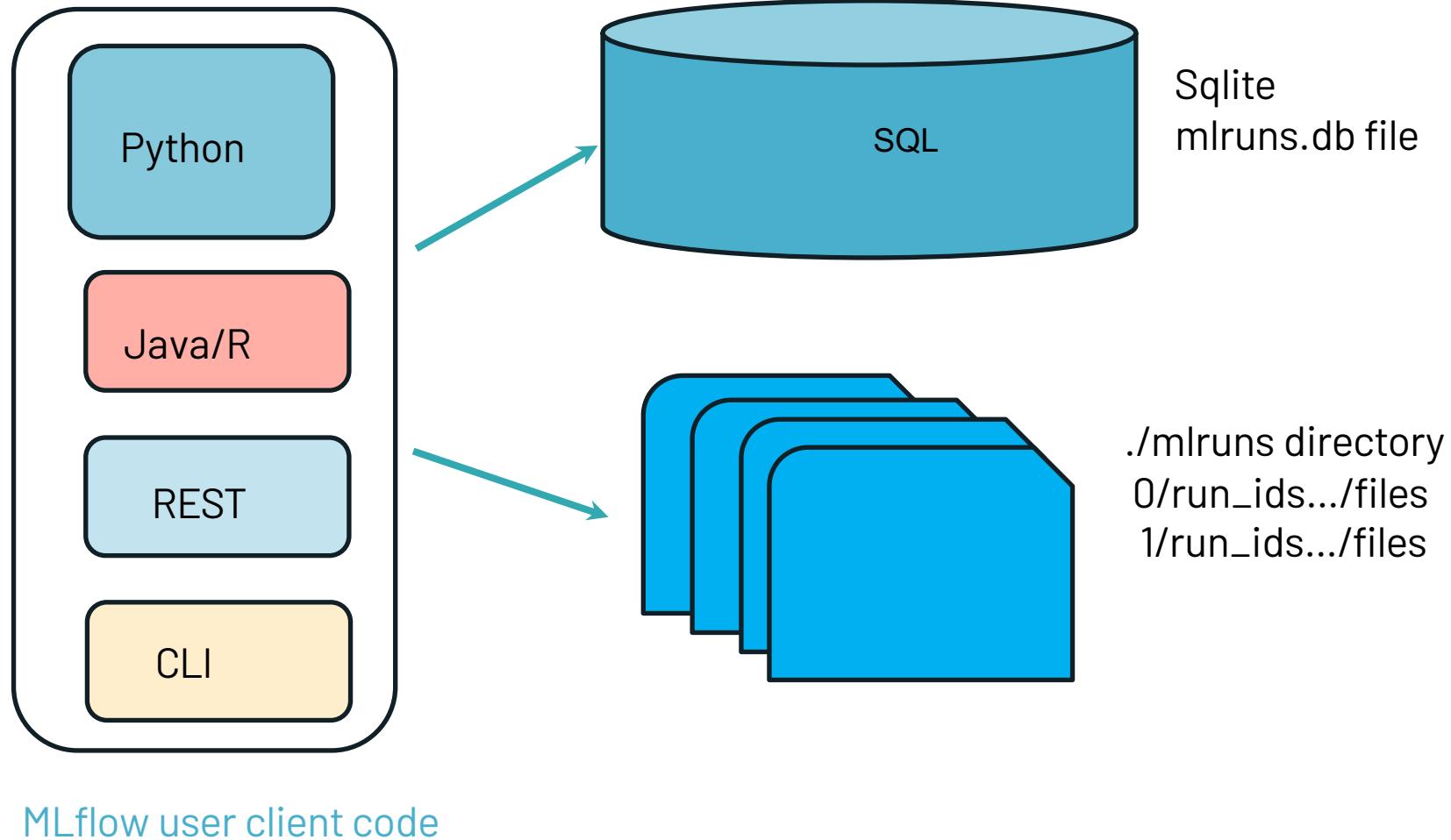
Track parameters, metrics, artifacts, output files & code version

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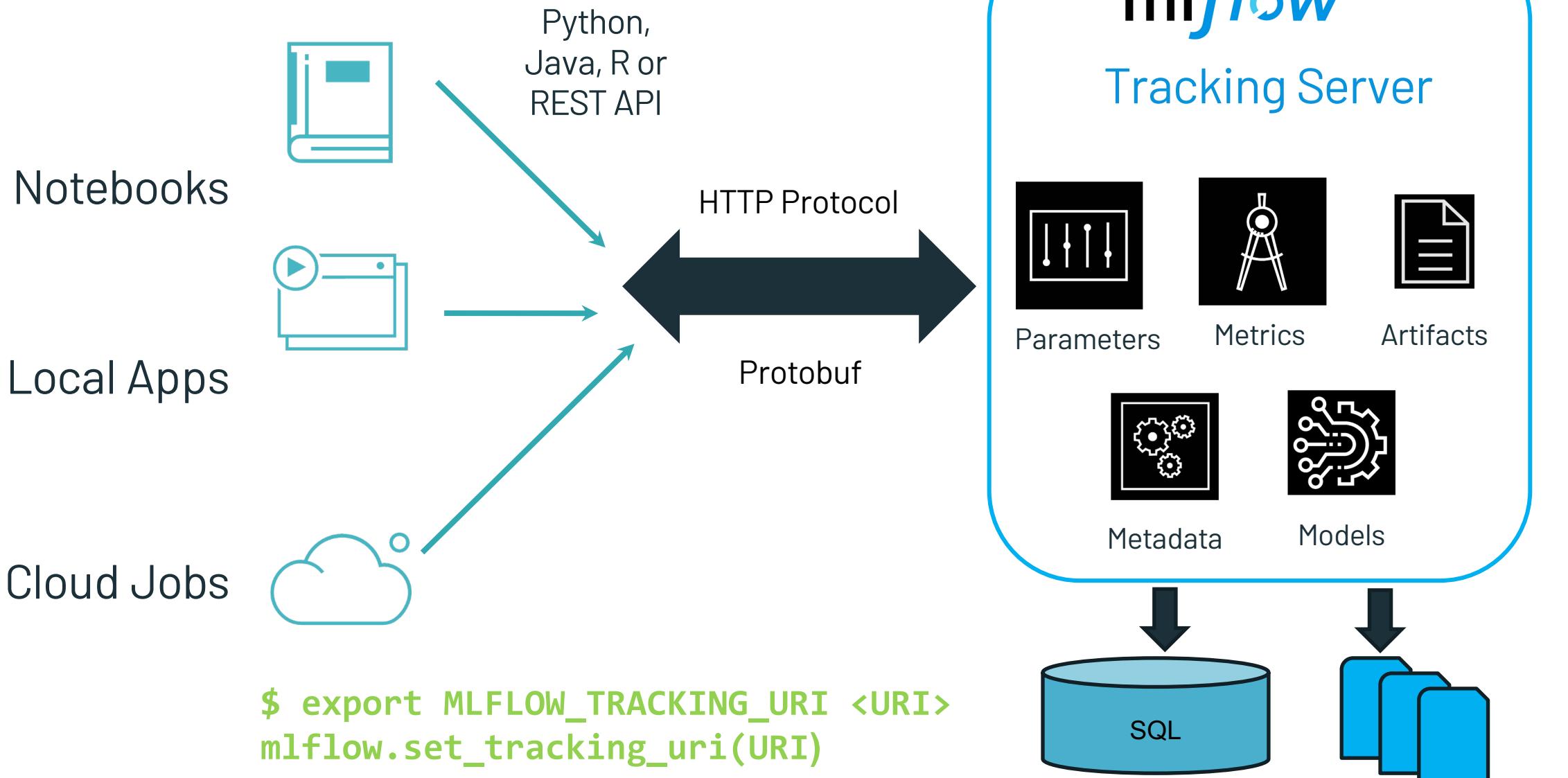
MLflow Tracking Server



MLflow Tracking Local Storage



MLflow Tracking Server



MLflow Tracking Server Storage

Entity (Metadata) Backend Store

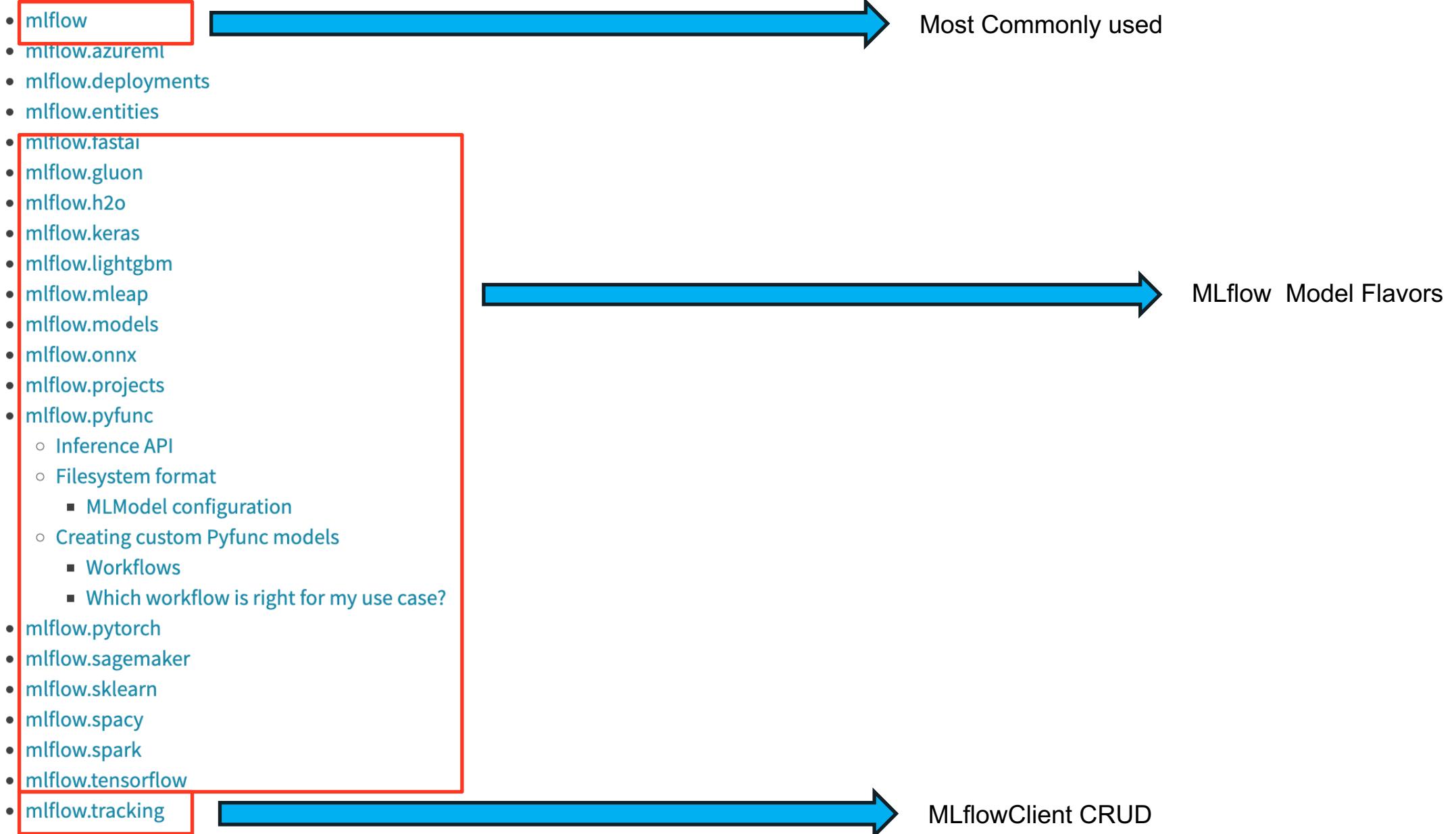
- FileStore (local filesystem)
 - ***mlruns*** directory by default
- SQLStore (via SQLAlchemy)
 - PostgreSQL, MySQL, SQLite
- MLflow Plugins Scheme
 - Customized Entity Metastore
- Managed MLflow on Databricks
 - MySQL on AWS and Azure

Artifact Store

- Local Filesystem
 - ***mlruns*** directory
- S3 backed store
- Azure Blob storage
- Google Cloud Storage
- DBFS artifact repo

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.



Built-In Model Flavors

MLflow provides several standard flavors that might be useful in your applications. Specifically, many of its deployment tools support these flavors, so you can export your own model in one of these flavors to benefit from all these tools:

- [Python Function \(python_function\)](#)
- [R Function \(crate\)](#)
- [H2O \(h2o\)](#)
- [Keras \(keras\)](#)
- [MLeap \(mleap\)](#)
- [PyTorch \(pytorch\)](#)
- [Scikit-learn \(sklearn\)](#)
- [Spark MLlib \(spark\)](#)
- [TensorFlow \(tensorflow\)](#)
- [ONNX \(onnx\)](#)
- [MXNet Gluon \(gluon\)](#)
- [XGBoost \(xgboost\)](#)
- [LightGBM \(lightgbm\)](#)



mlflow.sklearn

The `mlflow.sklearn` module provides an API for logging and loading scikit-learn models. This module exports scikit-learn models with the following flavors:

Python (native) pickle format

This is the main flavor that can be loaded back into scikit-learn.

mlflow.pyfunc

Produced for use by generic pyfunc-based deployment tools and batch inference.

mlflow.sklearn.get_default_conda_env(include_cloudpickle=False) [source]

Returns

The default Conda environment for MLflow Models produced by calls to `save_model()` and `log_model()`.

mlflow.sklearn.load_model(model_uri) [source]

Load a scikit-learn model from a local file or a run.

Parameters

model_uri -

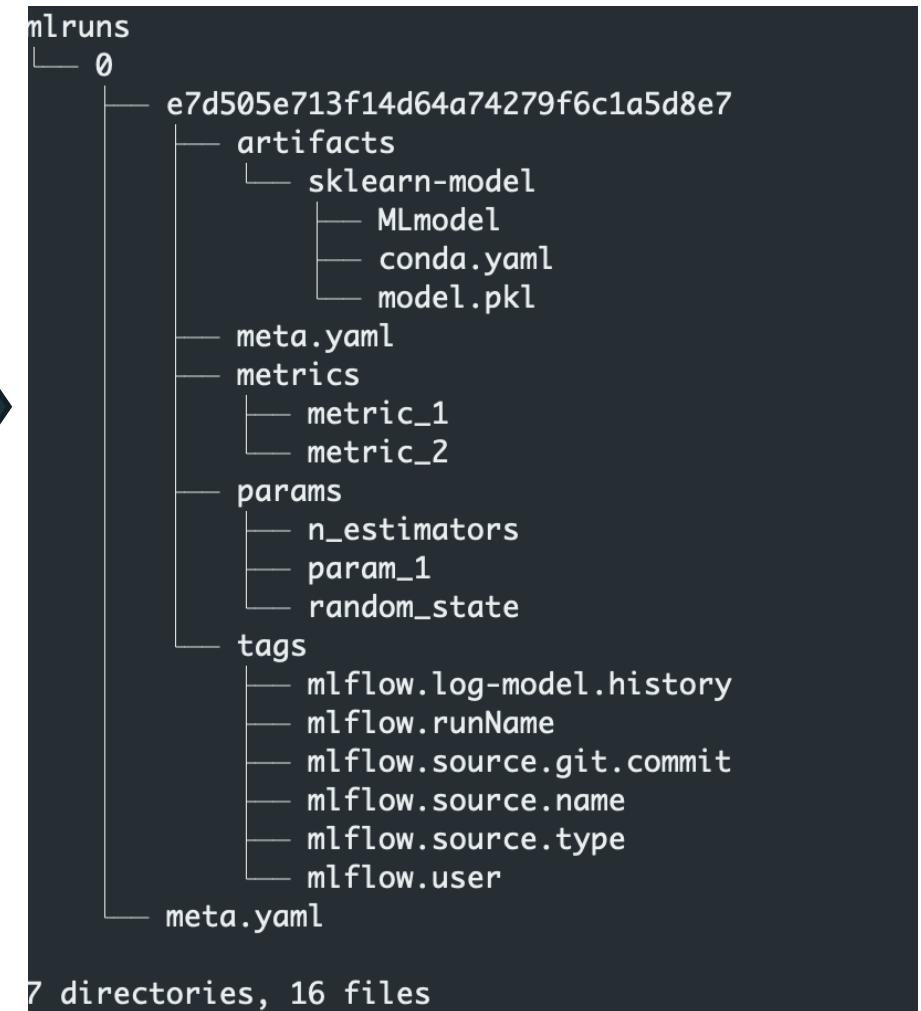
The location, in URI format, of the MLflow model, for example:

- `/Users/me/path/to/local/model`
- `relative/path/to/local/model`

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")
```



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> |
```

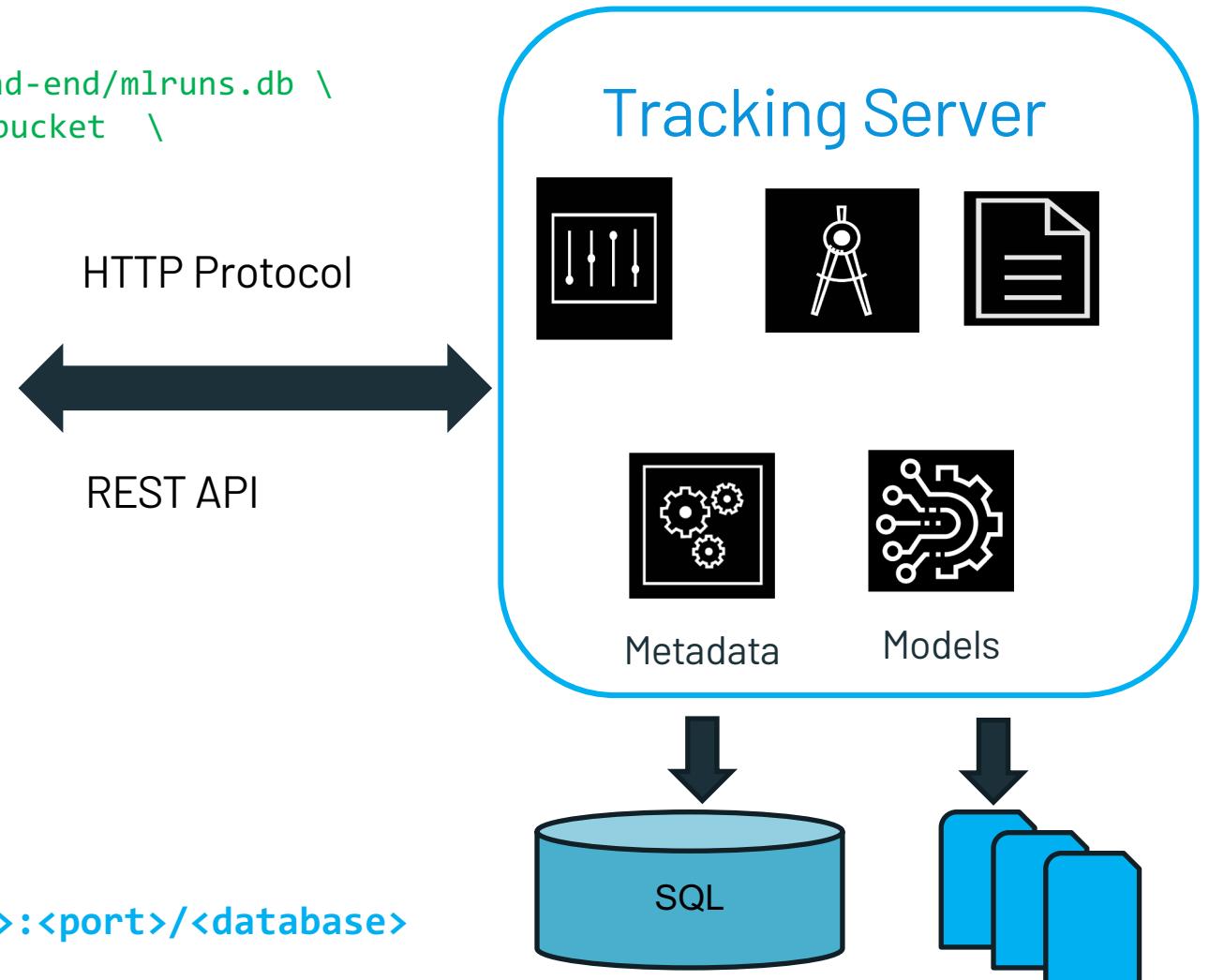
MLflow API Data Flow: Use Tracking Server SQLAlchemy backend store

```
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")
```

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

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



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 mlflow.tracking`
- `client = MLflowClient(**kwargs)`
- Metric, Param, Search etc

MLflow REST API

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

What Did We Talk About? **mlflow**TM

- 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](https://github.com/mlflow/mlflow)
- Join the [Slack channel](#)
- More [MLflow tutorials](#)

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<http://dbricks.co/dais2020eu>



MLflow Tracking Tutorials

<https://github.com/dmatrix/olt-mlflow>

Thank you! 😊

Q & A

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