

OPEN DATA SCIENCE CONFERENCE



mlflow Platform for Complete Machine Learning Lifecycle

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<https://dbricks.co/odsc-tutorial>
<https://mlflow.org>



Guest WiFi:
Password:

I have used **ML Frameworks** Before...



\$ whoami



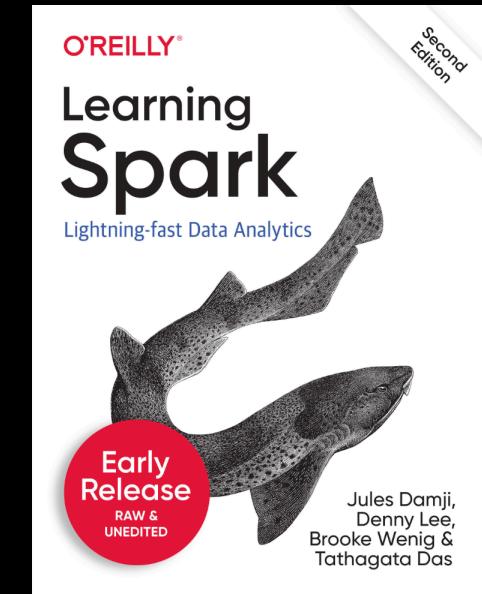
Apache Spark Developer & Community Advocate @ Databricks

Developer Advocate @ Hortonworks

Software engineering @ Sun Microsystems, Netscape, @Home, Excite@Home, VeriSign, Scalix, Centrify, LoudCloud/Opsware, ProQuest

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VISION

Accelerate innovation by unifying data science,
engineering and business

SOLUTION

Unified Data Analytics Platform

WHO WE ARE

- Original creators of   
- 2000+ global companies use our platform across big data & machine learning lifecycle

Outline

- Overview of ML development challenges
- How MLflow tackles these
- MLflow Components
- Managed MLflow ML + Registry Demo
- Q & A
- (Break?)
- Set up Environment
- Hands of Tutorial

Machine Learning Development is Complex

ML Development Challenges

1. Zoo of software tools
2. Tracking & reproducing results
3. Productionizing models
4. Scaling
5. Different from Traditional Software Development

Traditional Software

Goal: Meet a functional specification

Quality depends only on code

Typically pick one software stack

Machine Learning

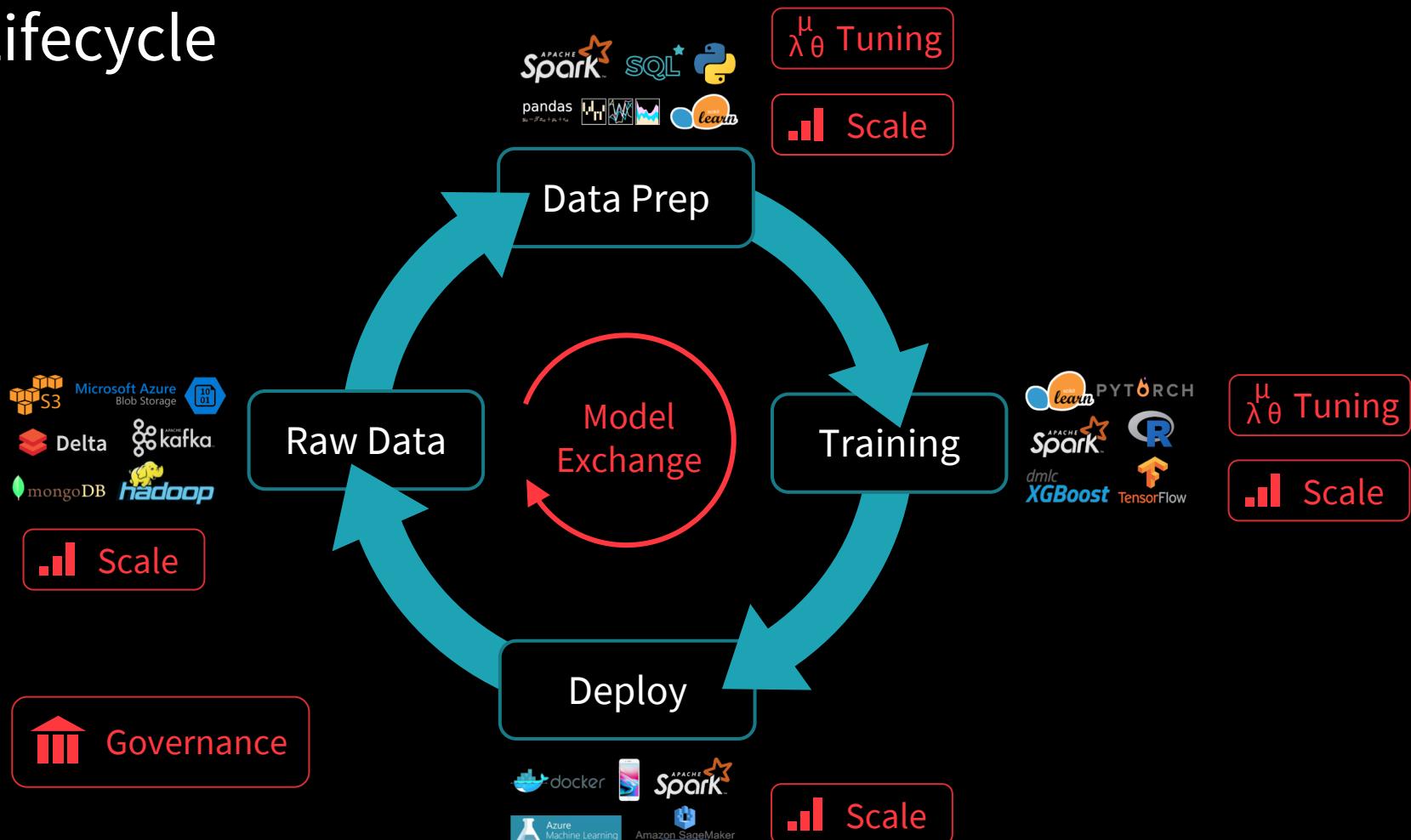
Goal: Optimize a metric (e.g., accuracy)
Constantly experiment to improve it

Quality depends on input data
and tuning parameters

Compare + combine many libraries,
models & algorithms for the same task



ML Lifecycle



Custom ML Platforms

Facebook FBLearn, Uber Michelangelo, Google TFX

+ 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. 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

Key enabler: built around REST APIs and 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)

MLflow Components

mlflow

Tracking

Record and query experiments: code, configs, results, ... etc.

mlflow

Projects

Packaging format for reproducible runs on any platform

mlflow

Models

General model format that supports diverse deployment tools

mlflow

Registry

Repository of named, versioned models w/tags, comments , etc

Model Development without MLflow

```
data    = load_text(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?

Key Concepts in 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?

MLflow Tracking API: Simple!

mlflow Tracking

Record and query experiments: code, configs, results, ...etc

```
import mlflow

# log model's tuning parameters

with mlflow.start_run():
    mlflow.log_param("layers", layers)
    mlflow.log_param("alpha", alpha)

# log model's metrics
mlflow.log_metric("mse", model.mse())
mlflow.log_artifact("plot", model.plot(test_df))
mlflow.tensorflow.log_model(model)
```

Model Development with MLflow is Simple!

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

mlflow.log_param("data_file", file)
mlflow.log_param("n", n)
mlflow.log_param("learning_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.mse < 1 and params.model = 'tree'". Below the search bar, there are sections for "Experiments" and "Default". The "Default" section shows a table of runs with columns: Data, User, Source, Version, Parameters, and Metrics. The table contains 36 rows of data, each representing a run with specific parameters like alpha, it_ratio, mse, c0, and c1, and metrics like mse and r2.

Data	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	0.597 0.25 0.762
2018-07-19 03:26:14	root	azure-demo	0.01	0.55	0.597 0.25 0.762
2018-07-19 03:25:51	root	azure-demo	0.01	0.75	0.597 0.25 0.762
2018-07-19 03:25:42	root	azure-demo	0.01	0.04	0.591 0.256 0.759
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	0.61	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
2018-07-17 08:13:30	root	azure-demo	0.01	0.75	0.597 0.25 0.762
2018-07-17 08:13:27	root	azure-demo	0.01	0.01	0.591 0.257 0.759
2018-07-17 08:08:05	root	azure-demo	0.01	0.01	0.591 0.257 0.759

Track parameters, metrics, output files & code version

Search using UI or API

MLflow Tracking



MLflow Tracking Backend Stores

1. Entity (Metadata) Store

- FileStore (local filesystem)
- SQLStore (via SQLAlchemy)
 - PostgreSQL, MySQL, SQLite

2. Artifact Store

- S3 backed store
- Azure Blob storage
- Google Cloud storage
- DBFS artifact repo

MLflow Components

mlflow

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Projects

Packaging format for reproducible runs on any platform

mlflow

Models

General model format that supports diverse deployment tools

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MLflow Projects Motivation

Diverse set of tools



Diverse set of environments

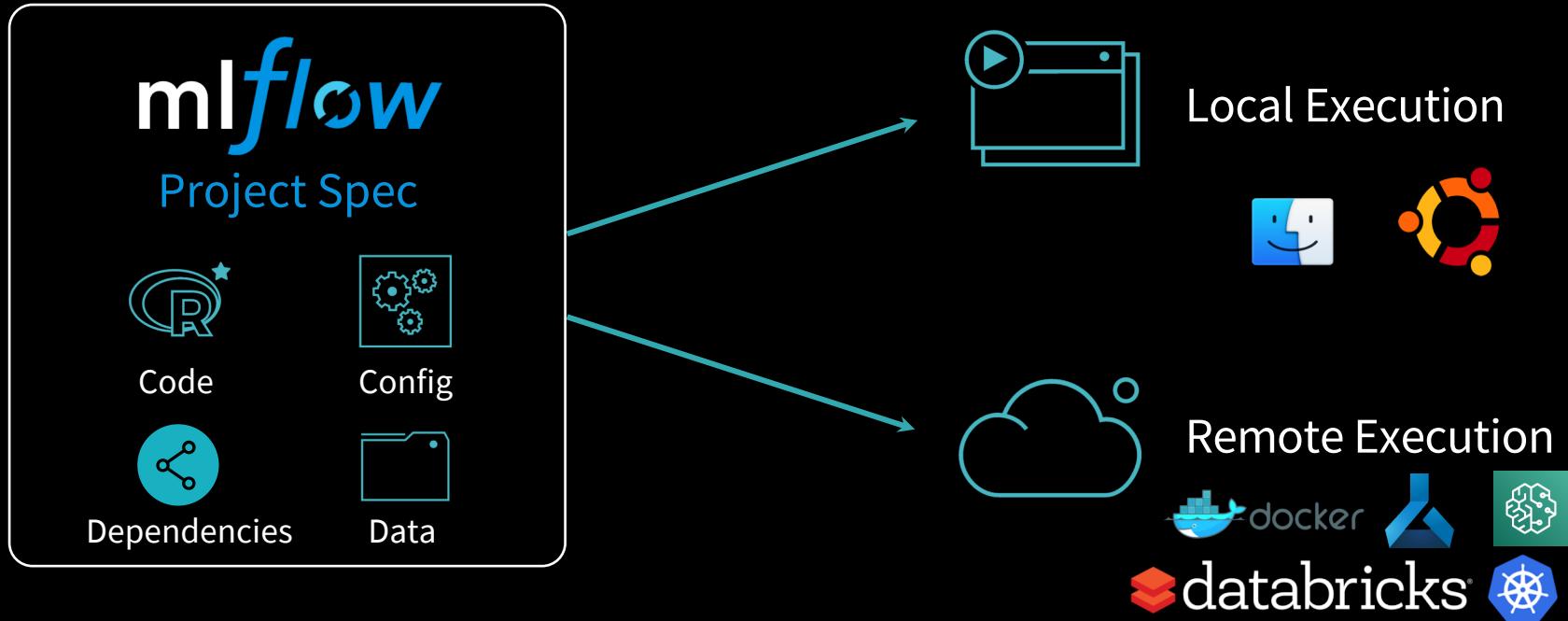


mlflow
Projects

Packaging format
for reproducible
runs
on any platform

Challenge: ML results difficult to reproduce

MLflow Projects



MLflow Projects

Packaging format for reproducible ML runs

- Any code folder or GitHub repository
- Optional MLproject file with project configuration

Defines dependencies for reproducibility

- Conda (+ R, Docker, ...) dependencies can be specified in MLproject
- Reproducible in (almost) any environment

Execution API for running projects

- CLI / Python / R / Java
- Supports local and remote execution

Example MLflow Project

```
my_project/
  └── MLproject
      ├── conda.yaml
      ├── main.py
      ├── model.py
      └── ...
```

```
conda_env: conda.yaml

entry_points:
  main:
    parameters:
      training_data: path
      lambda: {type: float, default: 0.1}
    command: python main.py {training_data} {lambda}
```

```
$ mlflow run git://<my_project> -P lambda=0.2
mlflow.run("git://<my_project>", ...)

mlflow run . -e main -P lambda=0.2
```

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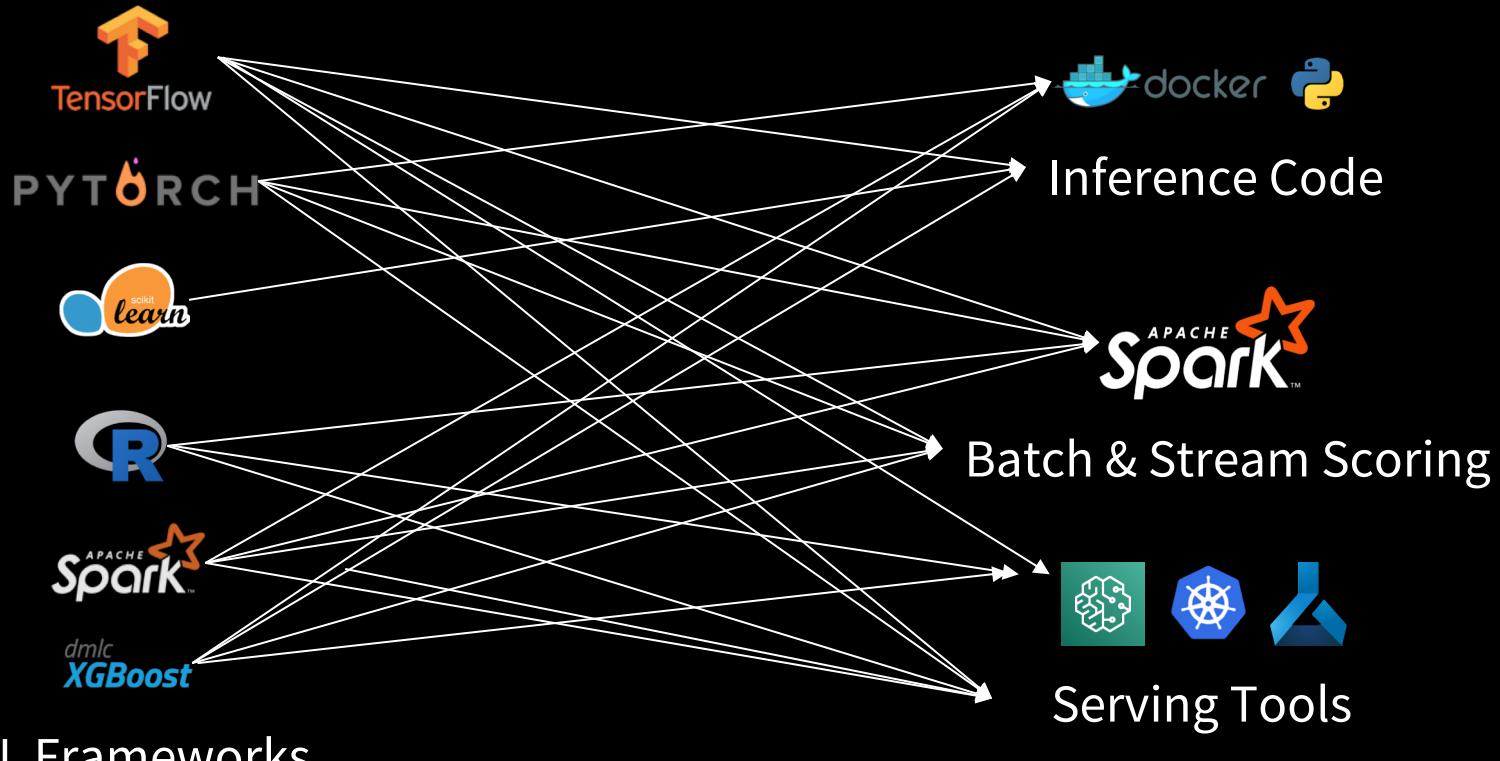
General model format that supports diverse deployment tools

mlflow

Registry

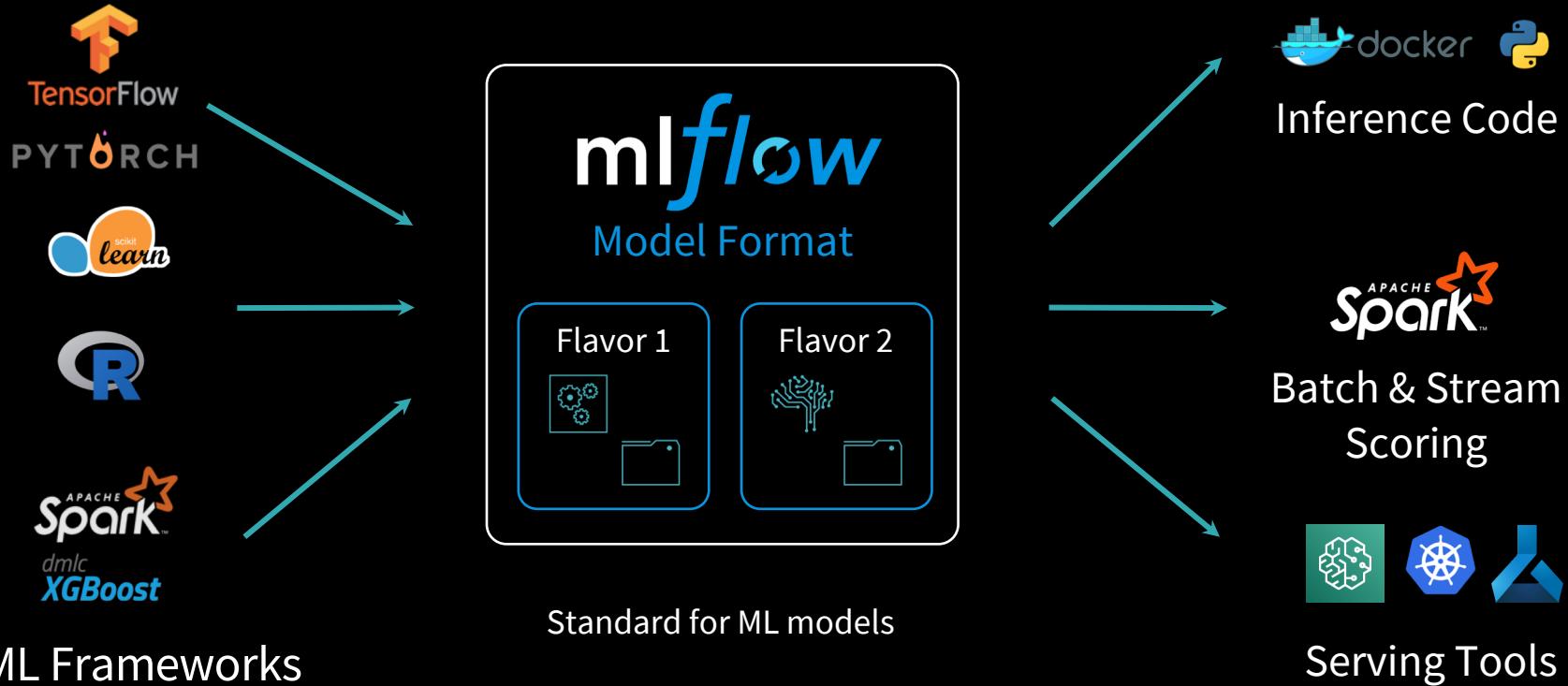
Repository of named, versioned models w/tags, comments , etc

MLflow Model Motivation

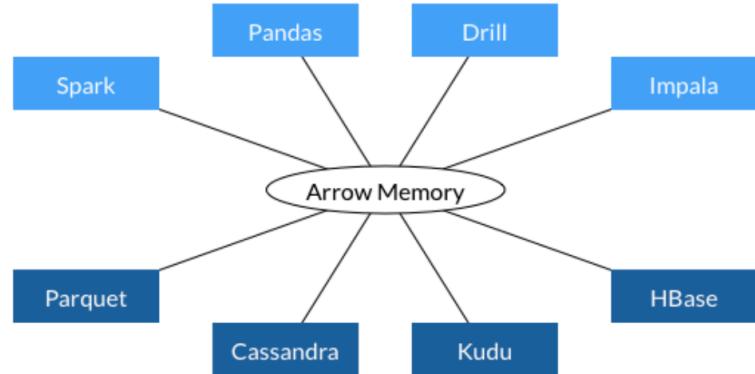
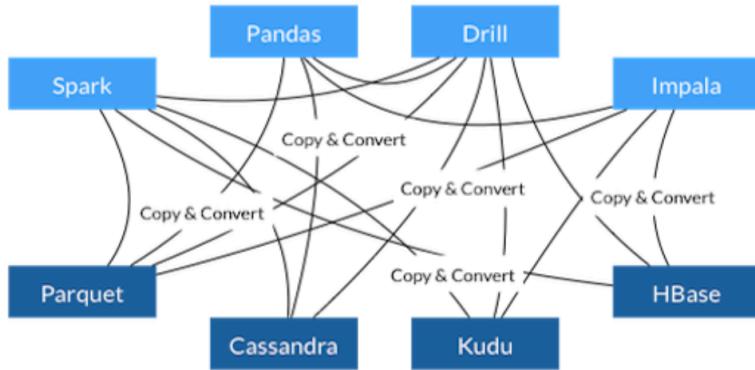


ML Frameworks

MLflow Models



Advantages of a Common Data Layer



- Each system has its own internal memory format
- 70-80% computation wasted on serialization and deserialization
- Similar functionality implemented in multiple projects

- All systems utilize the same memory format
- No overhead for cross-system communication
- Projects can share functionality (eg, Parquet-to-Arrow reader)

MLflow Models

Packaging format for ML Models

- Any directory with MLmodel file

Defines dependencies for reproducibility

- Conda environment can be specified in MLmodel configuration

Model creation utilities

- Save models from any framework in MLflow format

Deployment APIs

- CLI / Python / R / Java

Example MLflow Model

```
mlflow.tensorflow.log_model(...)
```

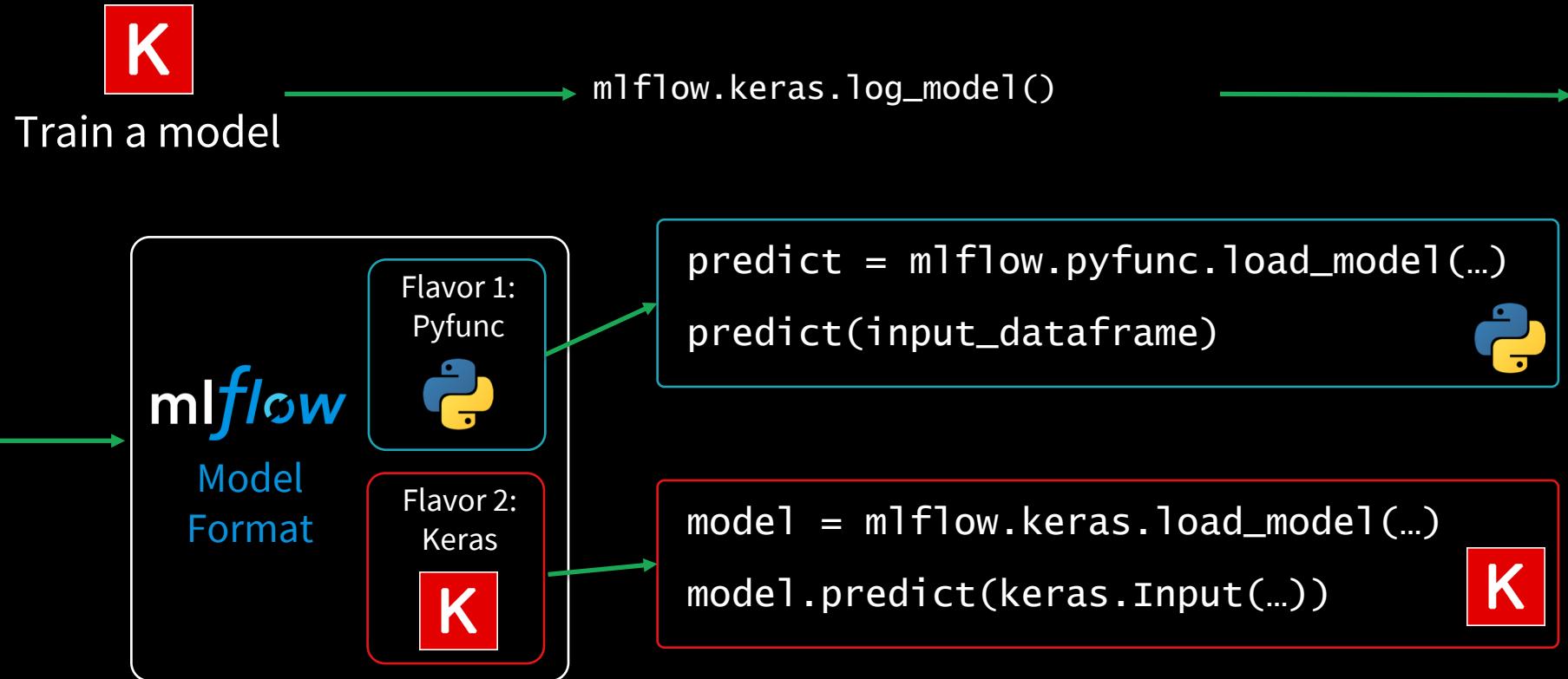
```
my_model/  
  └─ MLmodel
```

```
run_id: 769915006efd4c4bbd662461  
time_created: 2018-06-28T12:34  
flavors:  
  tensorflow:  
    saved_model_dir: estimator  
    signature_def_key: predict  
  python_function:  
    loader_module: mlflow.tensorflow
```

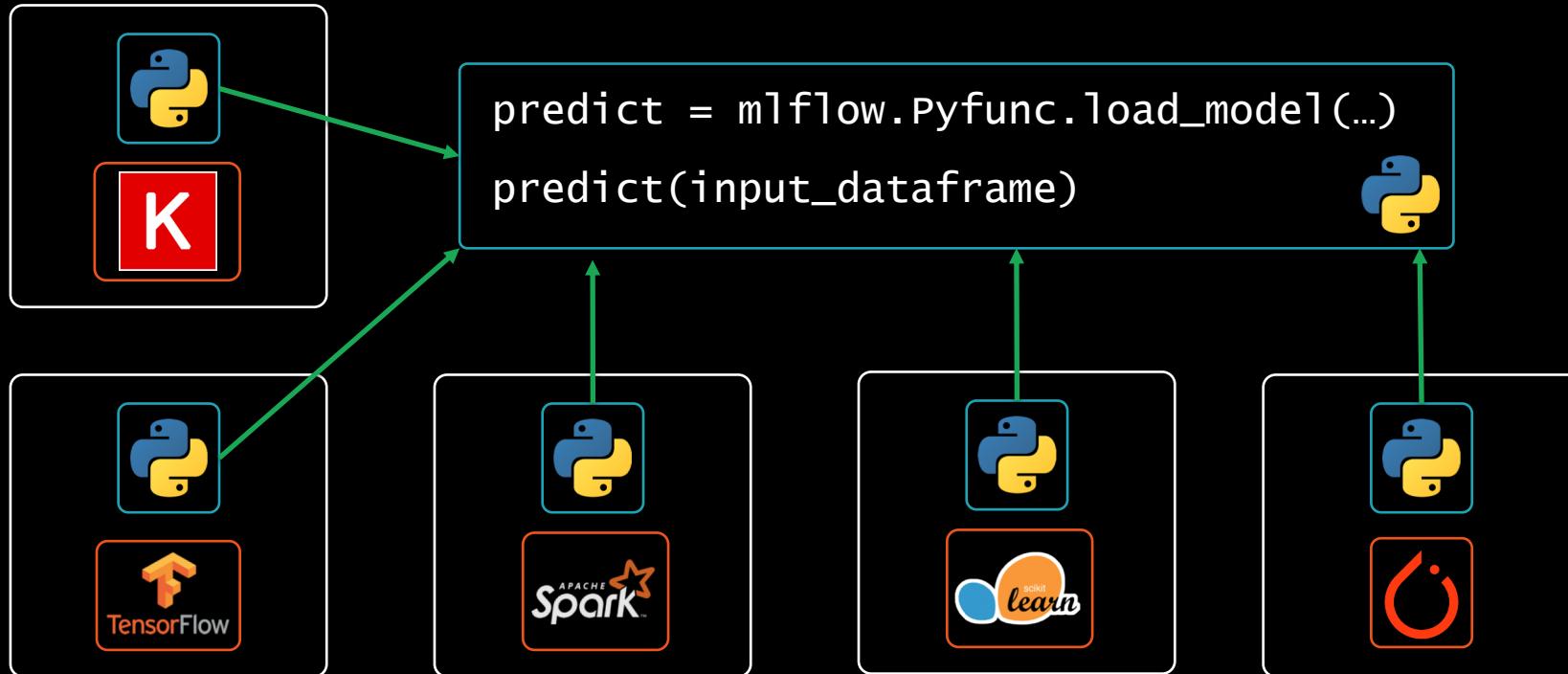
} Usable by tools that understand TensorFlow model format
} Usable by any tool that can run Python (Docker, Spark, etc!)

```
  └─ estimator/  
    └─ saved_model.pb  
  └─ variables/  
  ...
```

Model Flavors Example



Model Flavors Example



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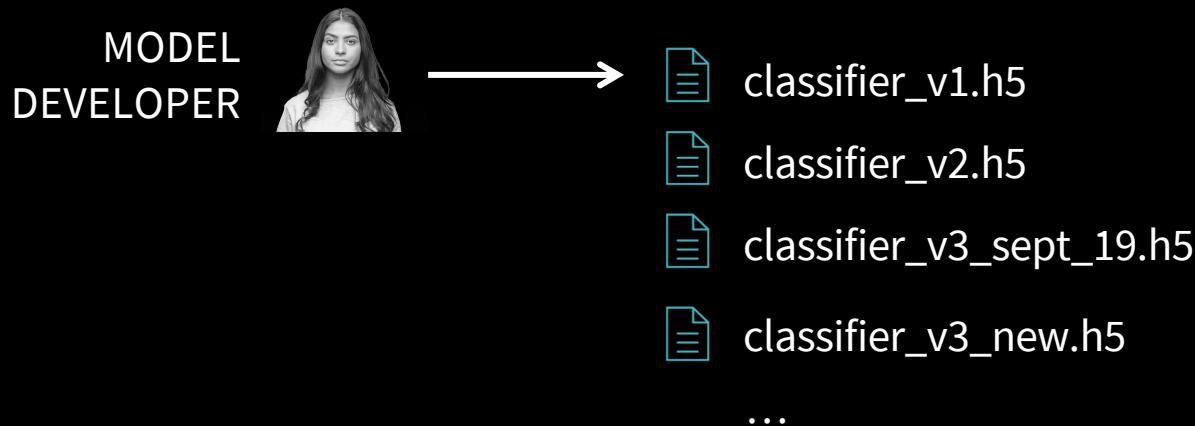
mlflow

Registry

Repository of named, versioned models w/tags, comments , etc

The Model Management Problem

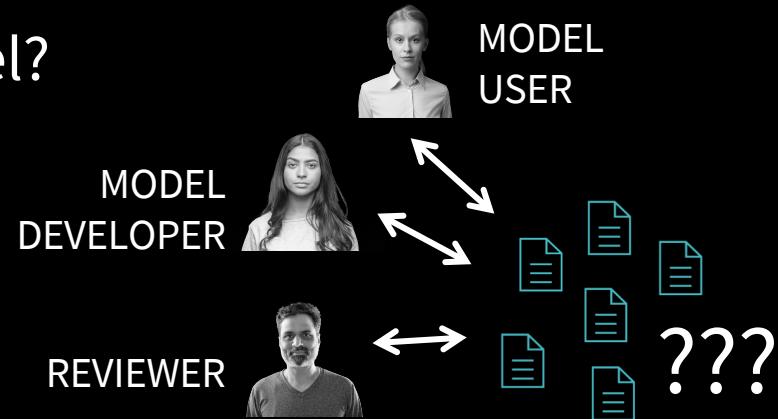
When you're working on one ML app alone, storing your models in files is manageable



The Model Management Problem

When you work in a **large organization** with **many models**, management becomes a major challenge:

- Where can I find the best version of this model?
- How was this model trained?
- How can I track docs for each model?
- How can I review models?



MLflow Model Registry

Repository of named, versioned models with comments & tags

Track each model's stage: dev, staging, production, archived

Easily load a specific version

Registered Models > Airline_Delay_SparkML ▾

Created Time : 2019-10-10 15:20:29 Last Modified : 2019-10-14 12:17:04

▼ Description [🔗](#)

Predicts airline delays (in minutes) using the best Spark RF model from the AutoML Toolkit.

▼ Versions [All](#) Active(1)

Version	Registered at	Created by	Stage
Version 1	2019-10-10 15:20:30	clemens@demo.com	Archived
Version 2	2019-10-10 21:47:29	clemens@demo.com	Archived
Version 3	2019-10-10 23:39:43	clemens@demo.com	Production
Version 4	2019-10-11 09:55:29	clemens@demo.com	None
Version 5	2019-10-11 12:44:44	matei@demo.com	Staging

Model Registry Workflow API

```
mlflow.register_model("runs:/e148278107274..832/artifacts/model",  
                      "EmailSpamClassifier")
```

MODEL
DEVELOPER



REVIEWERS,
CI/CD TOOLS



```
client = mlflow.tracking.MlflowClient()  
client.get_latest_versions(name = " EmailSpamClassifier",  
                           stages = [ " Production "])
```

DOWNSTREAM
USERS



AUTOMATED JOBS



REST SERVING

```
client = mlflow.tracking.MlflowClient()  
client.update_model_version(name = "EmailSpamClassifier ",  
                           version = 12,  
                           stage = "Production")
```

Model Registry Availability

Pull request available: tinyurl.com/registry-pr

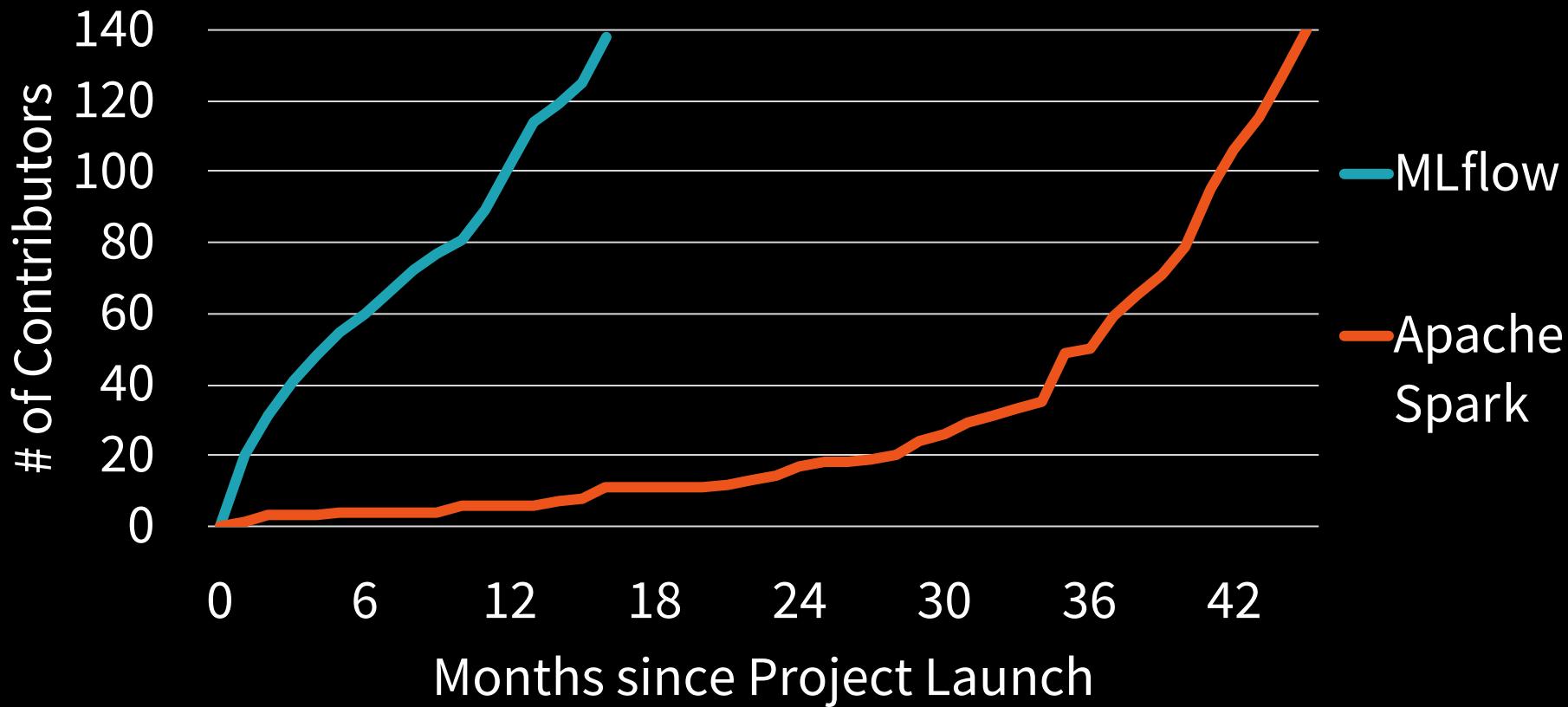
Available to Databricks customers

<https://mlflow.org/docs/latest/model-registry.html>

New in Last 6 Months

- MLflow 1.0 (and 1.1, 1.2, 1.3)
 - Model Registry
 - Support for TensorFlow 2.0
 - TensorFlow/Keras auto-logging
 - “Step” axis for metrics & Improved UI
 - Improved search capabilities
 - Support for ONNX models
 - Kubernetes, HDFS & Seldon Integrations

Project Contributors over Time



What Did We Talk About?

Workflow tools can greatly simplify the ML lifecycle

- Simplify lifecycle development
- Lightweight, open platform that integrates easily
- Available APIs: Python, Java & R (Soon Scala)
- Easy to install and use
- Develop locally and track locally or remotely
- Deploy locally, cloud, on premise...
- Visualize experiments



Our curriculum keeps pace with the platform.

PRIVATE CORPORATE TRAINING

PUBLIC TRAINING

CERTIFICATIONS

SELF-PACED TRAINING

<https://academy.databricks.com>

Setup Environment & Hands on Tutorials

<https://dbricks.co/odsc-tutorial>

<https://mlflow.org>



Thank You 😊

Q & A

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