



mlflow: Platform for Complete Machine Learning Lifecycle

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Outline

Overview of ML development challenges

How MLflow tackles these

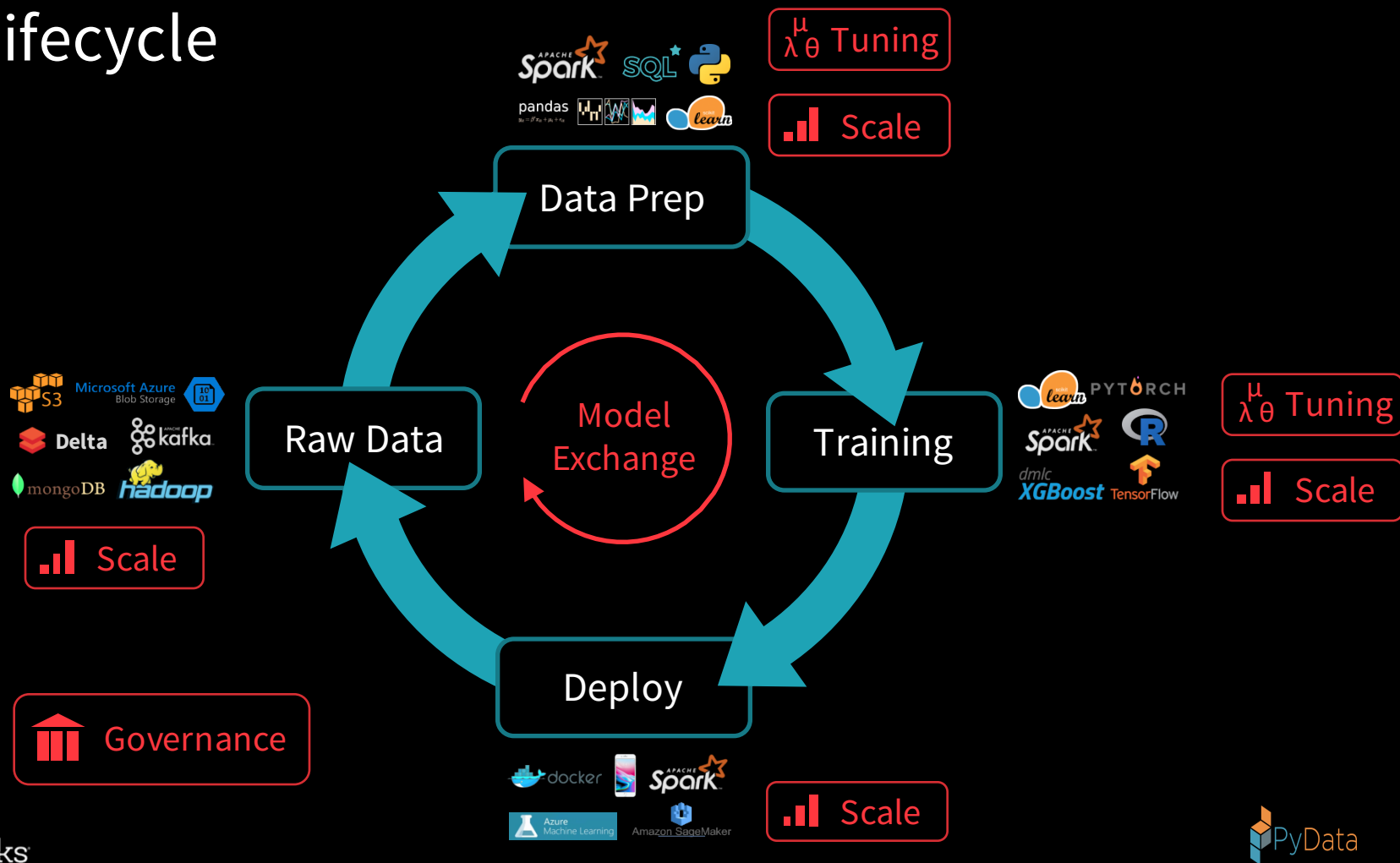
MLflow Components

Developer Experience & Demo

Ongoing Roadmap

Machine Learning Development is Complex

ML Lifecycle



Example

“I build 100s of models/day to lift revenue, using any library: MLlib, PyTorch, R, etc. There’s no easy way to see what data went in a model from a week ago, tune it and rebuild it.”

-- Chief scientist at ad tech firm

Custom ML Platforms

Facebook FBLearner, 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 any ML library & language
- Runs the same way anywhere (e.g., any cloud)
- Designed to be useful for 1 or 1000+ person orgs
- Simple, Easy-to-use, Developer Experience, and get started!

MLflow Design Philosophy

1. “API-first”, open platform

- Allow submitting runs, models, etc from any library & language
- Example: a “model” can just be a lambda function that MLflow can then deploy in many places (Docker, Azure ML, Spark UDF, ...)

Key enabler: built around REST APIs and CLI

MLflow Design Philosophy

2. Modular design

- Let people use different components individually (e.g., use MLflow's project format but not its deployment tools)
- Not monolithic, 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

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
```

mlflow

Experiments

Default

Artifacts

Experiments

Runs

Models

Jobs

mlflow

Experiments

Default

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Experiments

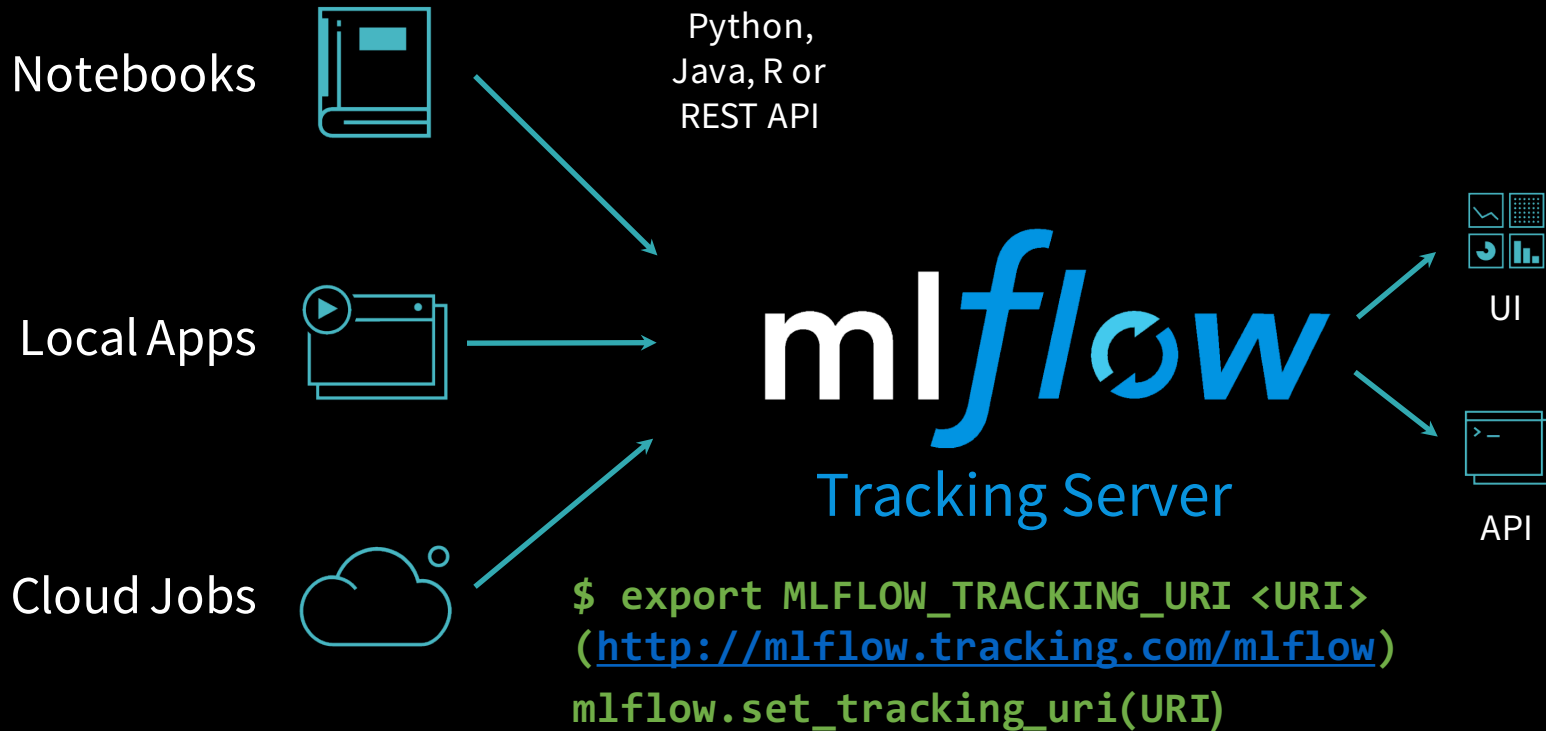
Default

mlflow

Track parameters, metrics,
output files & code version

Search using UI or API

MLflow Tracking



MLflow Projects Motivation

Diverse set of tools

PYTORCH



TensorFlow



APACHE
Spark

dmlc
XGBoost



Diverse set of environments



docker



Azure
Machine Learning



databricks

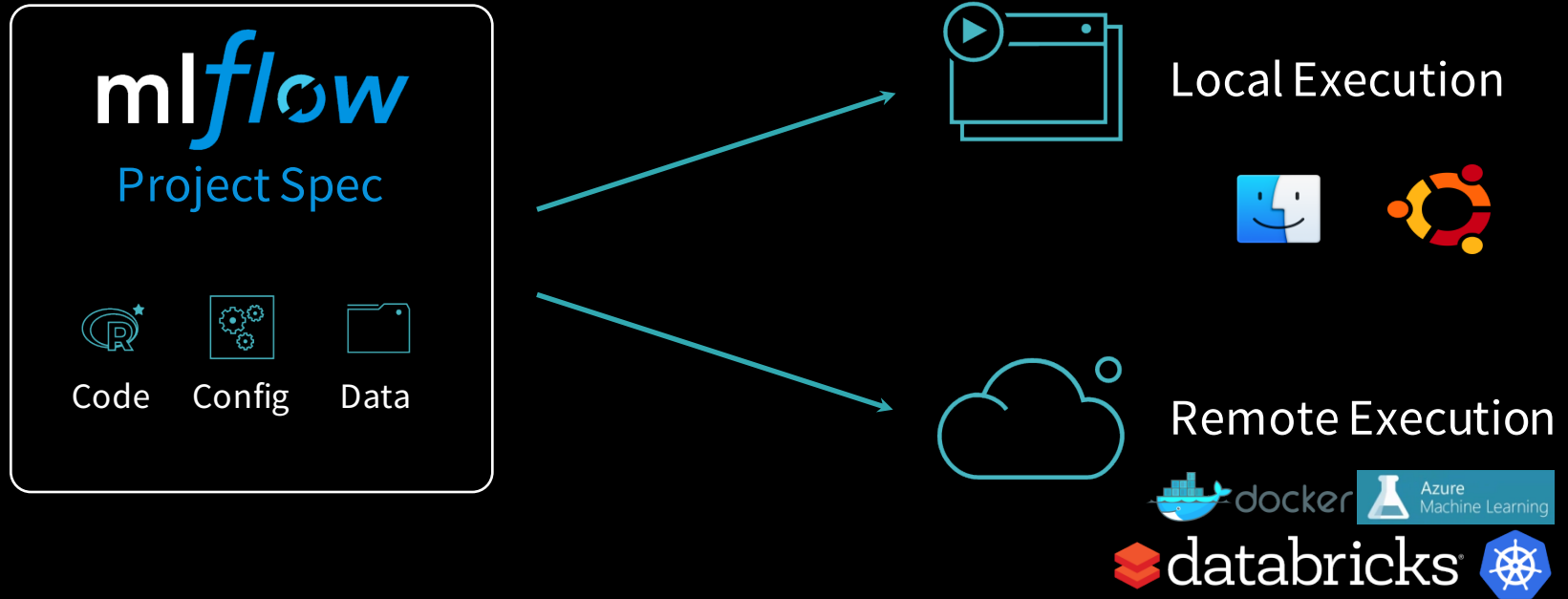


mlflow
Projects

Packaging format
for reproducible
runs
on any platform

Result: It is difficult to productionize and share.

MLflow Projects



Example MLflow Project

my_project/
├── MLproject

```
conda_env: conda.yaml
```

```
entry_points:
```

```
  main:
```

```
    parameters:
```

```
      training_data: path
```

```
      lambda: {type: float, default: 0.1}
```

```
    command: python main.py {training_data} {lambda}
```

├── conda.yaml
├── main.py
├── model.py
└── ...

```
$ mlflow run git://<my_project>
```

```
mlflow.run("git://<my_project>", ...)
```

MLflow Models



ML Frameworks



Standard for ML models



Inference Code



Batch & Stream Scoring



Amazon SageMaker

Serving Tools



Example MLflow 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/
 ...

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

Developer Experience & Demo



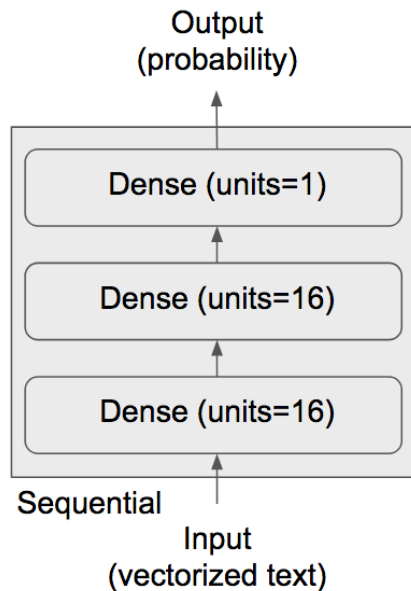
Binary Classification of
IMDB Movie Reviews Using
Keras Neural Network Model

https://dbricks.co/keras_imdb

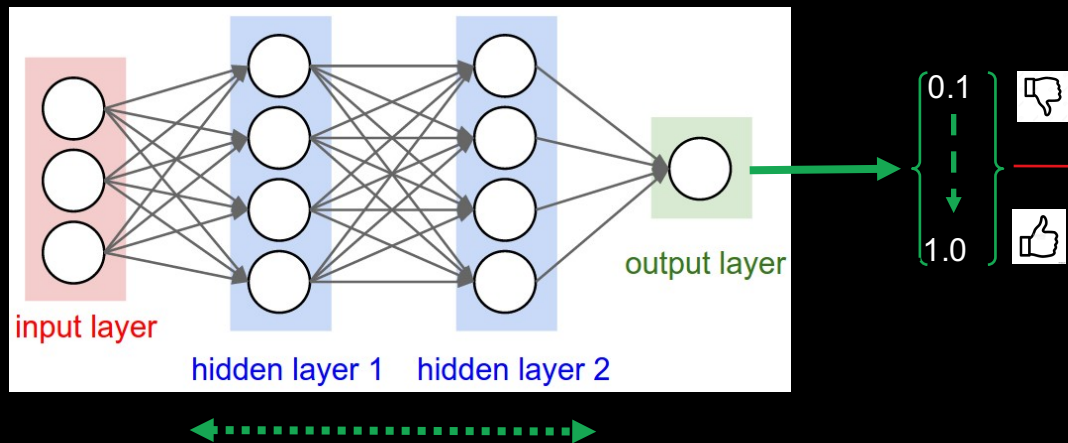
<https://github.com/dmatrix/jsd-mlflow-examples/>

MLflow Baseline & Experiment Models

Model	Units	Epochs	Loss Function	Hidden Layers
Base	16	20	binary_crossentropy	1
Experiment-1	32	30	binary_crossentropy	3
Experiment-2	32	20	mse	3



MLflow Baseline & Experiment Models



Ongoing MLflow Roadmap

- TensorFlow, Keras, PyTorch, H2O, MLlib integrations ✓
- Java and R MLflow Client language APIs ✓
- Multi-step workflows ✓
- Hyperparameter tuning ✓
- Integration with Databricks Tracking Server ✓
- Support for other Data Store (e.g., MySQL) ✓
- Data source API based on Spark data sources
- Model metadata & management

Just released v8.0.1

- Faster & Improved UI
- Extended Python Model as Spark UDF
- Persist model dependencies as Conda Environment

Learning More About MLflow

`pip install mlflow` to get started

Find docs & examples at mlflow.org

tinyurl.com/mlflow-slack

What Did We Talk About? **mlflow**

Workflow tools can greatly simplify the ML lifecycle

- Improve usability among data scientists and engineers
- Simplify lifecycle development
- Lightweight, open platform that integrates easily
- Available APIs: Python, Java & R
- Easy to install and use
- Develop locally and track locally or remotely



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Thank You ☺

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