mlflow : Platform for Complete Machine Learning Lifecycle

Mani Parkhe & Tomas Nykodym

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databricks

Outline

Overview of ML development challenges

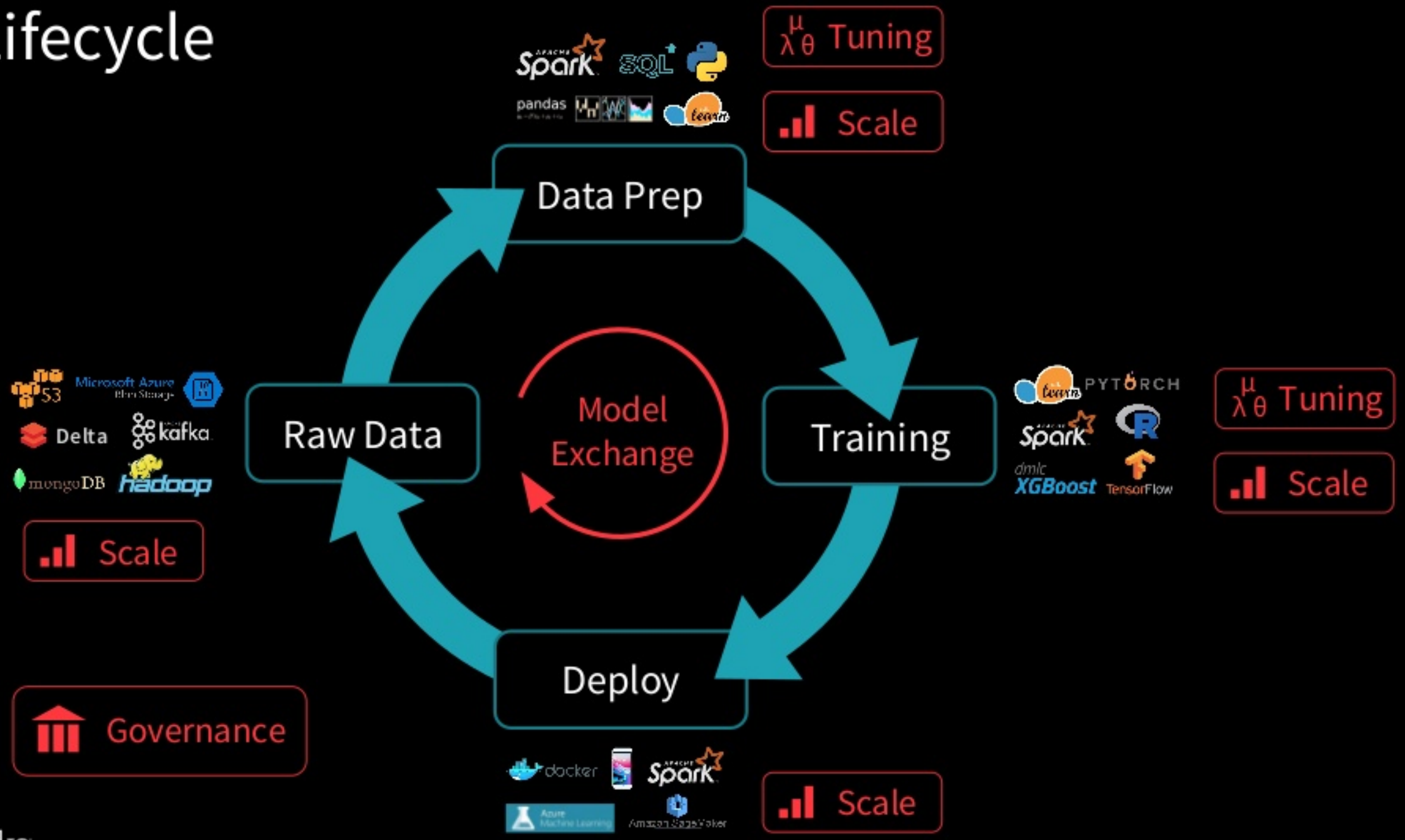
How MLflow tackles these

MLflow components

How to get started

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

Example

“Our company has 100 teams using ML worldwide. We can’t share work across them: when a new team tries to run some code, it often doesn’t even give the same result.”

-- Large consumer electronics 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

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

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 Tracking

mlflow Tracking

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

```
import mlflow

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

  # train model

  mlflow.log_metric("mse", model.mse())
  mlflow.log_artifact("plot", model.plot(test_df))
  mlflow.tensorflow.log_model(model)
```

Demo

Goal: Predict Price of Airbnb Listings

listing attributes

bathrooms: 1
bedrooms: 2
accommodates: 4
total_reviews: 45
cleanliness_rating: 9
location_rating: 10
checkin_rating: 10
zip_code: 94105

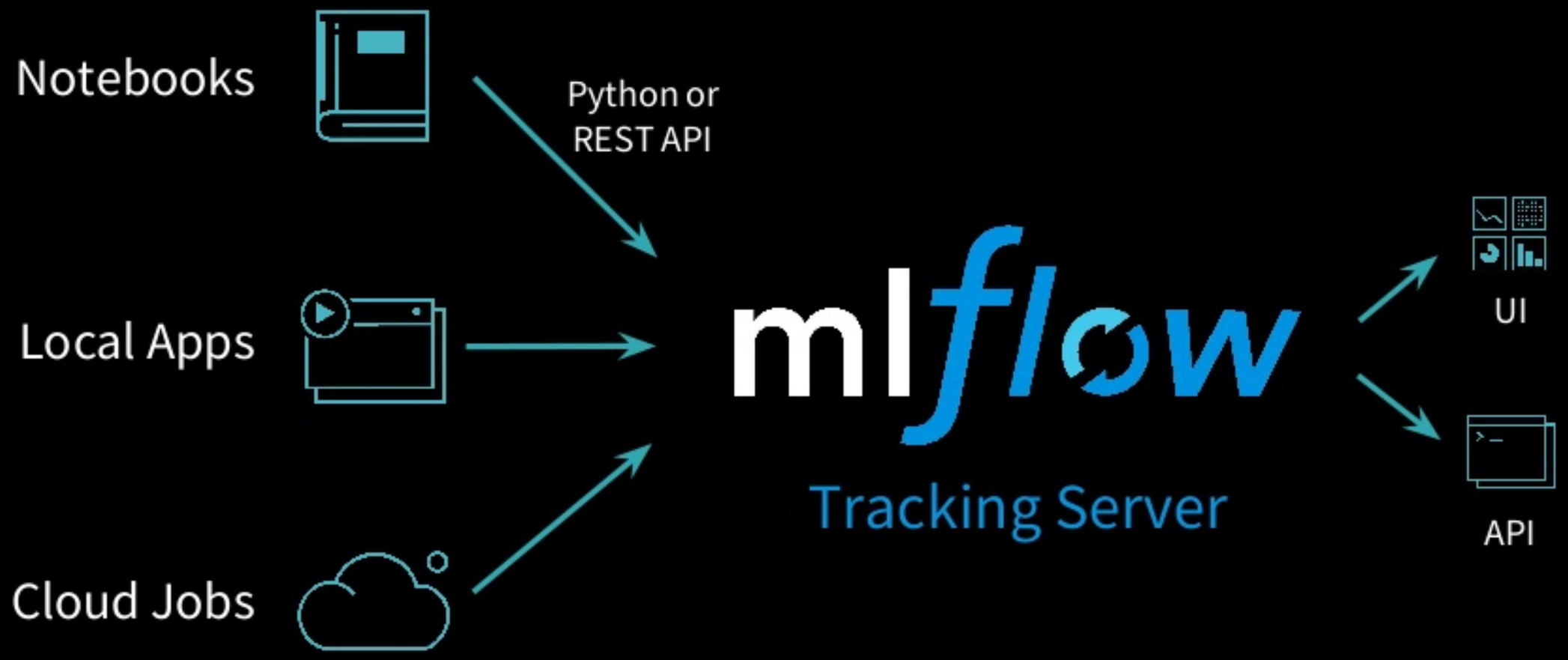
$f(x)$

Model

→ **price:** 150

based on data from insideairbnb.com

MLflow Tracking



Key Concepts in Tracking

Parameters: key-value inputs to your code

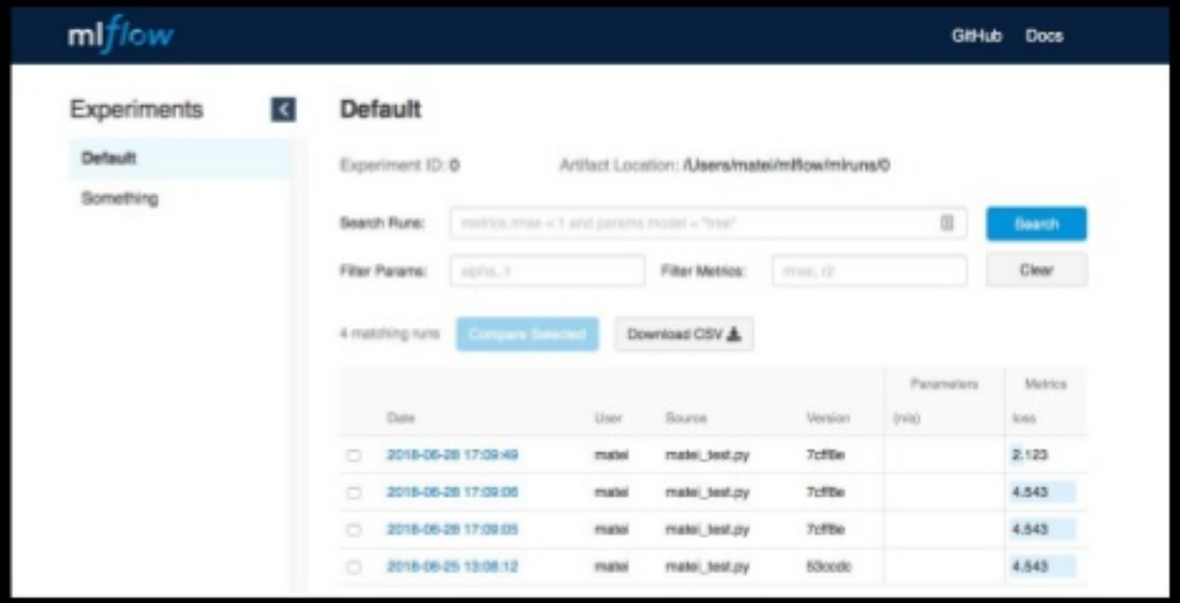
Metrics: numeric values (can update over time)

Tags and Notes: additional information about a run

Artifacts: arbitrary files, including data and models

Source: what code ran?

Version: what of the code?



MLflow backend stores

1. **Entity Store**
   - FileStore (local and REST)
   - Database backed (coming soon)

2. **Artifact Repository**
   - S3 backed store
   - Azure Blob storage
   - Google Cloud storage
   - DBFS artifact repo

Learning More About MLflow

`pip install mlflow` to get started

Find docs & examples at **mlflow.org**

tinyurl.com/mlflow-slack

Break

MLflow Deep Dive Part #2

Closer look at MLflow Projects and Models

mlflow Tracking

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

mlflow Projects

Packaging format for reproducible runs on any platform

mlflow Models

General model format that supports diverse deployment tools

MLflow Deep Dive Part #2

Outline

2.1 MLflow Projects

- Motivation
- Quick Overview
- Examples
- Demo

2.2 MLflow Models

- Motivation
- Quick Overview
- About Flavors
- Examples
- Demo

2.1 MLflow Projects

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MLflow Projects Motivation

Diverse set of tools

PYTORCH

TensorFlow

learn

APACHE Spark

dmlc XGBoost

R

Diverse set of environments

docker

Azure Machine Learning

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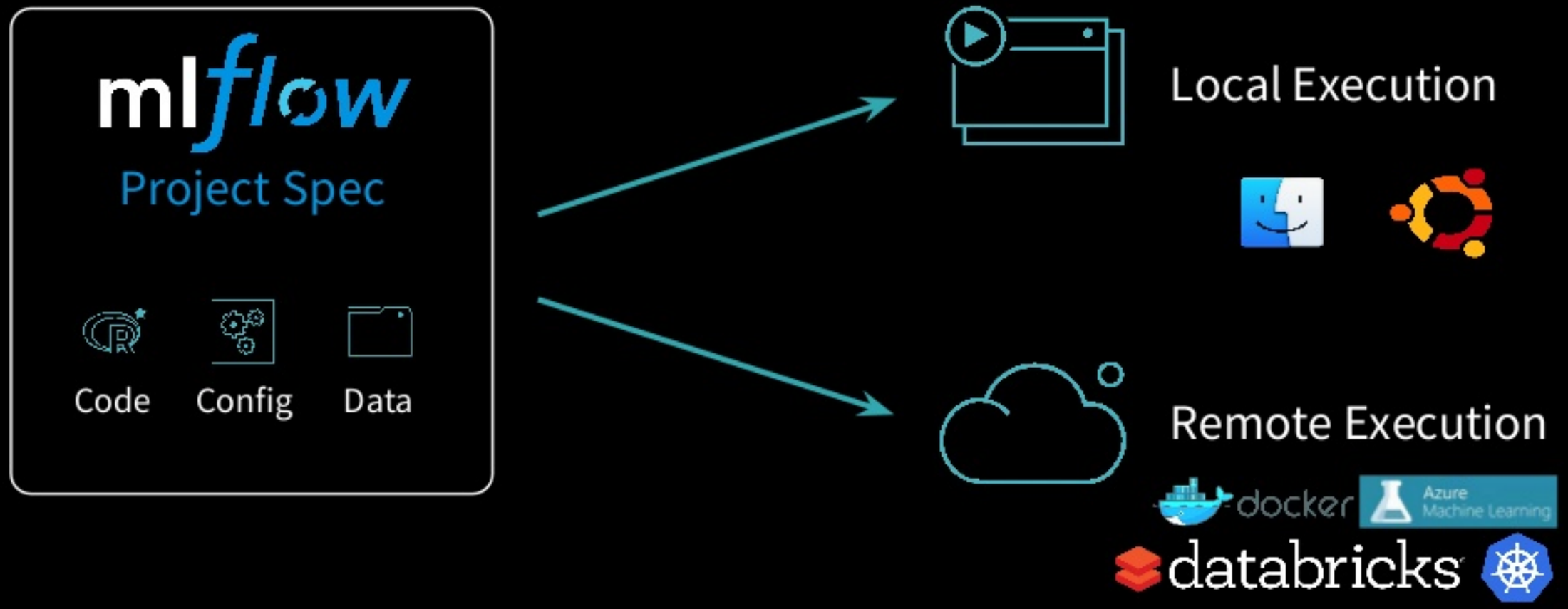
Result: It is difficult to productionalize and share.

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 locally or remote

- CLI / Python / R / Java
  - `mlflow run . -e train …`
  - `mlflow.projects.run(., “train”, ...)`

Example MLflow Project

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

```yaml
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>

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

Airbnb Example Revisited

We have 2 other data scientists working on the project

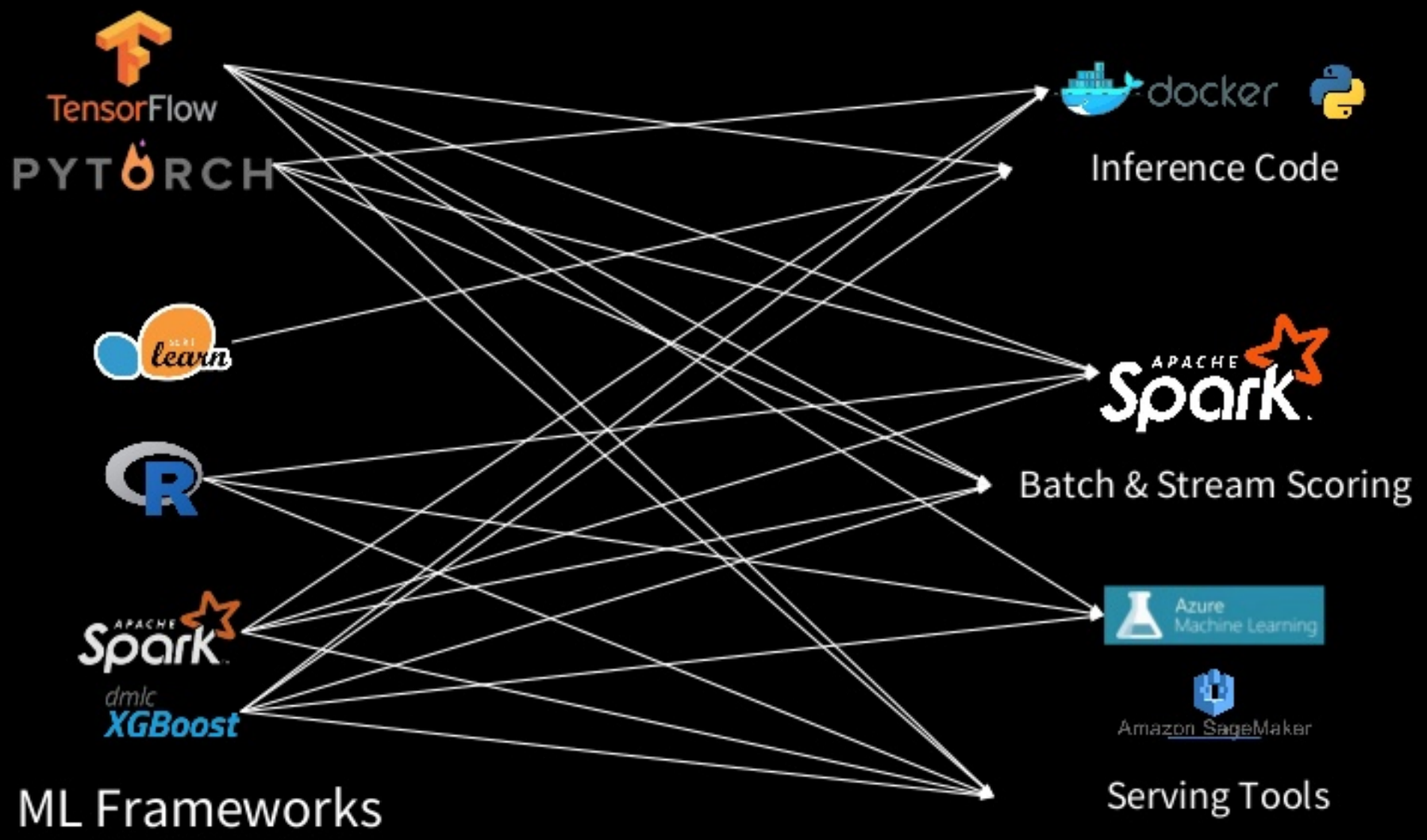
- Aaron used XGBoost in python
- Amy used Keras in R
- They provided their code as MLflow project on github

Let's test their code!

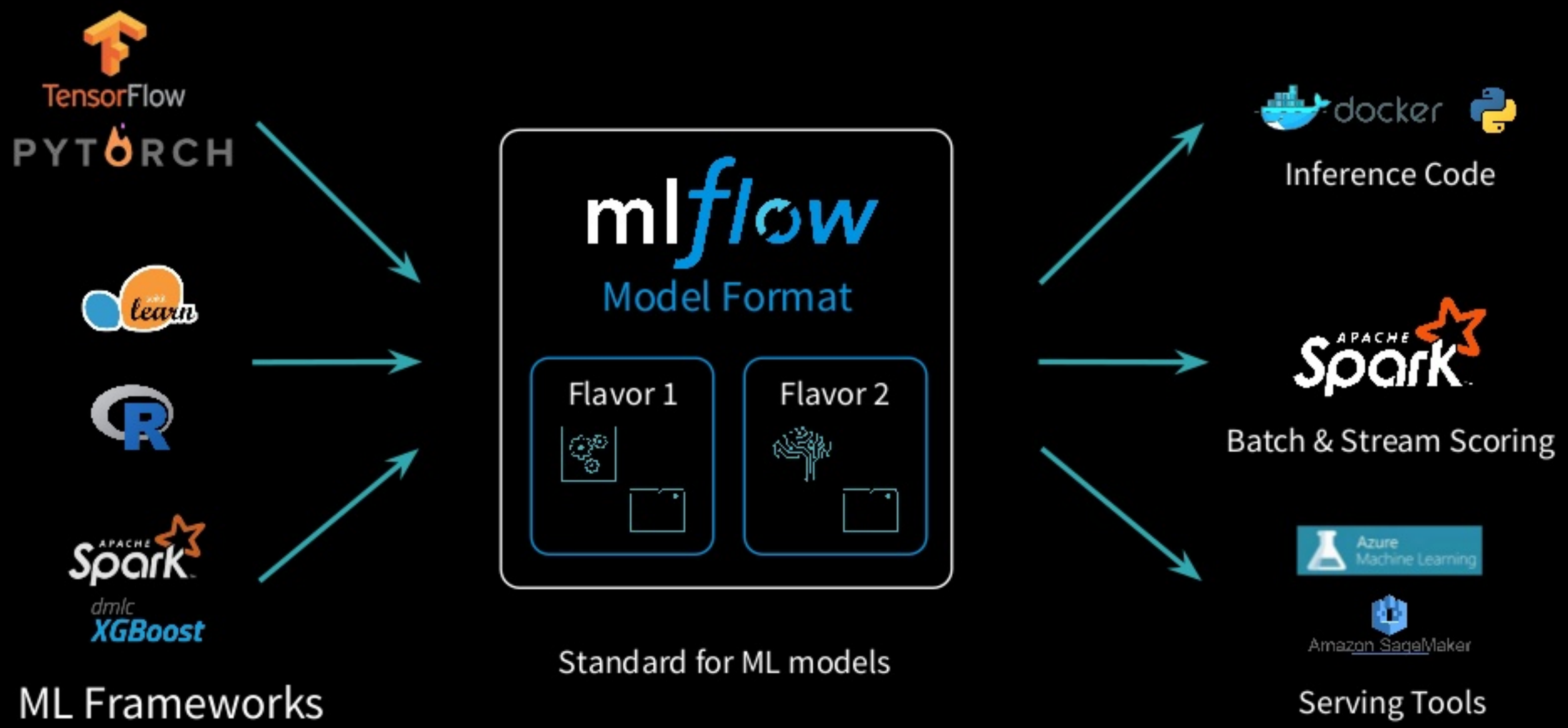
2.2 MLflow Models

- Motivation
- Quick Overview
- About Flavors
- Examples
- Demo

MLflow Models Motivation



MLflow Models



MLflow Models

Packaging format for ML Models

- Any directory with MLmodel file
- Different flavors for different models

Defines dependencies for reproducibility

- Conda (+ R, Docker, … ?) dependencies can be specified in MLproject
- Deployable (almost) anywhere

Deployment APIs

- CLI / Python / R / Java
  - `mlflow pyfunc serve …`
  - `mlflow.pyfunc.load(...).predict()`

Example MLflow Model

```
my_model/
├── MLmodel
│
│
│
│
│
│
└── estimator/
    ├── saved_model.pb
    └── variables/
        ...
```

```yaml
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!)

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

About Those Flavors

Models can generate several flavors

- Spark ML model generates spark, mleap and pyfunc flavors

Generic flavors provide abstraction layer

- pyfunc can be served locally, as spark_udf, on Azure ML, …
- By generating pyfunc flavor we get all above

Different Flavors Can be Loaded By Different Languages

- pyfunc in python, mleap in Java, crate in R, Keras in python and R

PyFunc - Generic Python Model

PyFunc is saved as “just a directory”:

```
./model_dir/
    ./MLmodel: configuration
    <code>: code packaged with the model (specified in the MLmodel file)
    <data>: data packaged with the model (specified in the MLmodel file)
    <env>: Conda environment definition (specified in the MLmodel file)
```

Model loader specified in MLmodel file:

Arbitrary python code loaded dynamically at runtime

Loaded Pyfunc is “just an object” with a predict method:

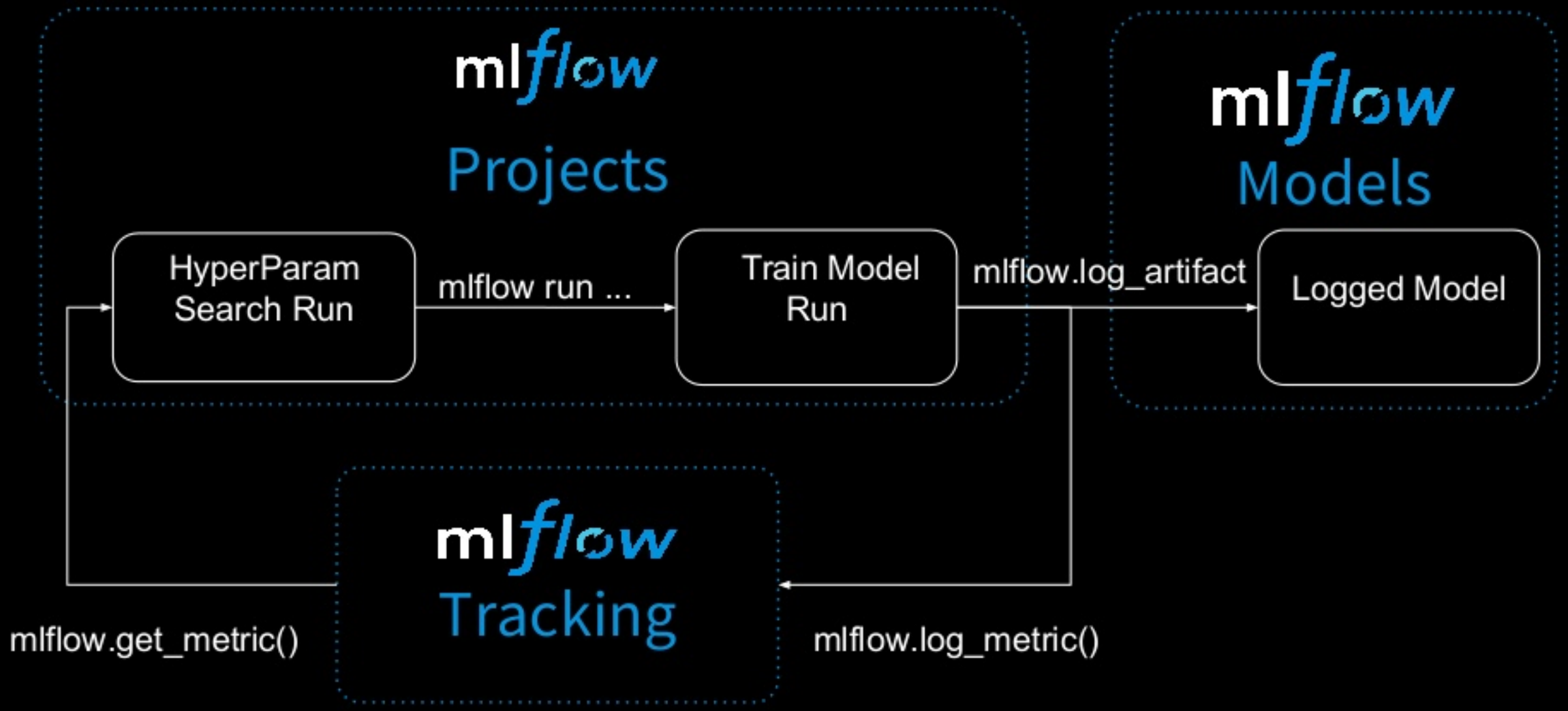
```
predict(pandas.DataFrame) -> pandas.DataFrame | numpy.array
```

Airbnb Example Revisited (Again)

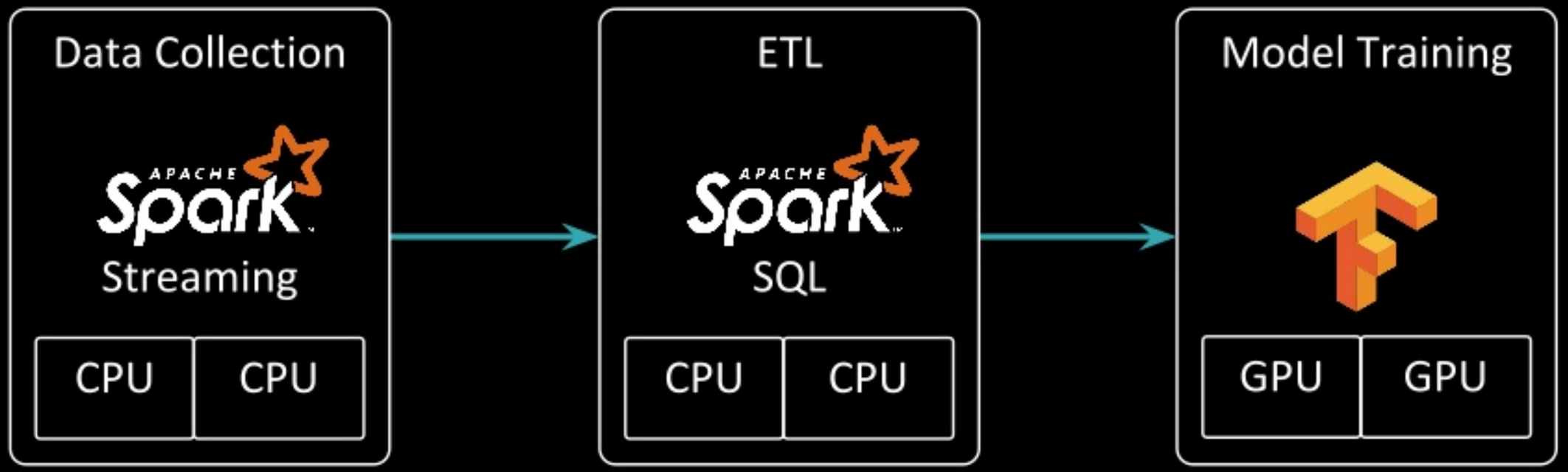
Let's put our models to production!

- Predict from cli
- Set up a real time REST API prediction server
- Score big data in Spark

Advanced MLFlow - HyperParameters



Advanced MLFlow - Multistep Workflow



Get started with MLflow

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Ongoing MLflow Roadmap

- TensorFlow, Keras, PyTorch, H2O, MLlib integrations ✔
- Java and R language APIs ✔
- Multi-step workflows
- Hyperparameter tuning
- Data source API based on Spark data sources
- Model metadata & management

Conclusion

Workflow tools can greatly simplify the ML lifecycle

- Improve usability for *both* data scientists and engineers
- Same way software dev lifecycle tools simplify development

Learn more about MLflow at mlflow.org

mlflow

Thank you!

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)
- Easy to integrate into existing ML platforms & workflows

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