MLOps and LLM Observability - Day 2

Karthikeyan Vaiyapuri

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Overview

Today's Learning Objectives

01

Set up complete MLOps environment with industry- standard tools

02

Master MLflow for experiment tracking and model management

03

Implement model versioning and dataset management

04

Hands-on practice with real MLflow workflows

Objectives

Production-Ready Environment

01 **Consistency:** Same environment across development, testing, production

02 **Reproducibility:** Anyone can recreate your results

03 **Scalability:** Easy to deploy and scale applications

04 **Collaboration:** Team members work with identical setups

What is Anaconda?

- **Package manager** for Python and R
- **Environment manager** for isolated development
- **Pre-installed libraries** for data science
- **Cross-platform** support (Windows, Mac, Linux)

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Introduction to MLflow

What is MLflow?

Open-source platform for ML lifecycle management

Experiment tracking and comparison

Model packaging and deployment

Model registry for version control

MLflow Components

- **MLflow Tracking:** Record and query experiments
- **MLflow Projects:** Package ML code for reuse
- **MLflow Models:** Deploy models to various platforms
- **MLflow Registry:** Centralized model store

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MLflow Architecture

Core Components Overview

MLFlow Tracking	MLFlow Projects	MLFlow Models	MLFlow Registry
• Experiments • Runs • Parameters • Metrics	• Code Package • Dependencies • Entry Points	• Model Format • Deployment • Serving	• Model Store • Versioning • Stage Mgmt

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MLflow Installation and Setup

Installation Methods

pip install mlflow

conda install -c conda-forge mlflow

pip install mlflow[extras]

Verify Installation

mlflow --version

mlflow ui

Configuration Options

Options

Tracking Server: Remote or local

Backend Store: SQLite, MySQL, PostgreSQL

Artifact Store: Local, S3, Azure, GCS

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Flask Integration with MLflow

Why Flask + MLflow?

Benefits

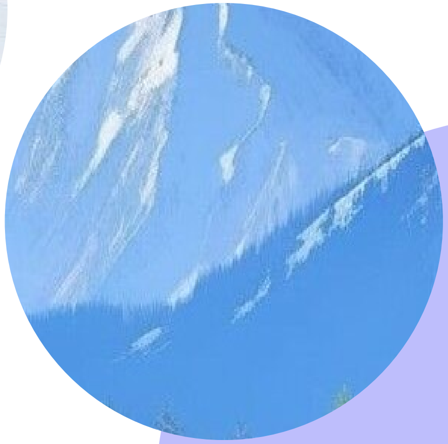
- **Model serving** through REST APIs
- **Integration** with MLflow model registry
- **Custom deployment** logic
- **Lightweight** web framework

Key Integration Points

- **Load models** from MLflow registry
- **Track predictions** back to MLflow
- **Monitor model performance**
- **A/B test** different model versions

Example Architecture

```
Client Request → Flask API → MLflow Model → Response
      ↓
MLflow Tracking ← Prediction Logs ← Model Metrics
```



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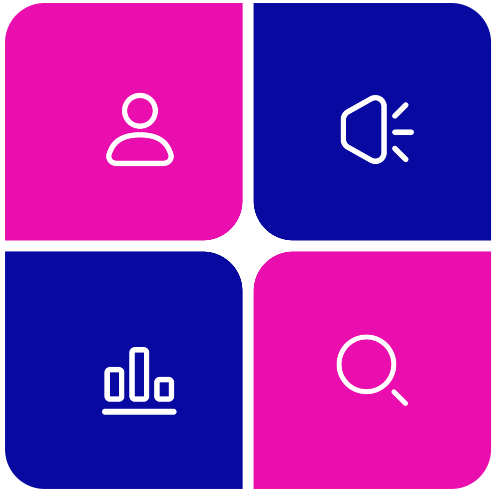
MLflow Tracking Fundamentals

Key Concepts

Experiment: Collection of related runs

Parameters: Input values (hyperparameters)

Artifacts: Files (models, images, data)



Run: Single execution of ML code

Metrics: Numeric values that change over time

Concepts Breakdown

Tracking Workflow

Workflow Steps

1. **Start experiment** or use default

2. **Log parameters** before training

3. **Log metrics** during/after training

4. **Save artifacts** (model, plots, data)

5. **End run** and review results

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Logging Parameters and Metrics

Parameters vs Metrics

Comparison

Parameters	Metrics
Static values	Dynamic values
Set once per run	Can change over time
Hyperparameters	Performance measures
String/Number	Numeric only

Code Examples

```python
import mlflow

# Start run
with mlflow.start_run():
    # Log parameters
    mlflow.log_param("learning_rate", 0.01)
    mlflow.log_param("n_estimators", 100)

    # Log metrics
    mlflow.log_metric("accuracy", 0.95)
    mlflow.log_metric("loss", 0.05)

    # Log multiple metrics
    mlflow.log_metrics({
        "precision": 0.92,
        "recall": 0.88
    })
```

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Artifact Management

What are Artifacts?

01

Model files: Trained models, weights

02

Data files: Datasets, preprocessed data

03

Plots/Images: Visualizations, reports

04

Code files: Scripts, notebooks

Types

Logging Artifacts

```
# Log single file
mlflow.log_artifact("model.pkl")

# Log directory
mlflow.log_artifacts("plots/", artifact_path="visualizations")

# Log model with metadata
mlflow.sklearn.log_model(
    model,
    "model",
    registered_model_name="my_model"
)
```

Artifact Storage

Storage Solutions

Local filesystem (default)

Cloud storage (S3, Azure, GCS)

Network filesystems

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Model Versioning Strategy

Why Version Models?

01 Track model evolution

02 Enable rollbacks

03 Compare performance

04 Reproducibility

05 Compliance and auditing

Versioning Levels

1. Code versioning: Git commits

2. Data versioning: Dataset snapshots

3. Model versioning: MLflow registry

4.Environment versioning: Docker images

Best Practices

- Semantic versioning (v1.2.3)
- Document changes

- Tag important versions
- Automate versioning

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MLflow Model Registry

Registry Features

Centralized model store

Version management

Stage transitions
(Staging → Production)

Model lineage
tracking

Approval workflows

Model Stages

None → Staging → Production → Archived

Registry Operations

```
# Register model
mlflow.register_model(
    "runs:/12345/model",
    "MyModel"
)

# Transition stage
client = mlflow.MlflowClient()
client.transition_model_version_stage(
    name="MyModel",
    version=1,
    stage="Production"
)
```

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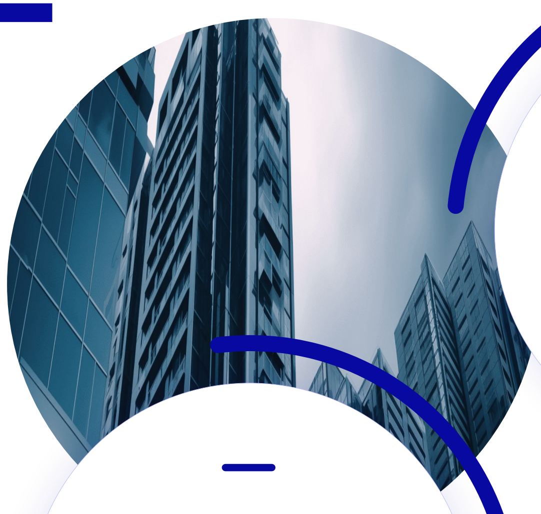
Dataset Versioning with MLflow

Dataset Tracking Challenges

Challenges

Large file sizes

Data drift detection



Lineage tracking

Storage efficiency

MLflow Dataset Features

```python
import mlflow.data
from mlflow.data.pandas_dataset import PandasDataset

# Create dataset
dataset = mlflow.data.from_pandas(
    df,
    source="data/train.csv",
    name="training_data"
)

# Log dataset
with mlflow.start_run():
    mlflow.log_input(dataset, context="training")
```

Dataset Versioning Benefits

01 Automatic checksums

02 Schema validation

03 Source tracking

04 Experiment reproducibility

Benefits

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Experiment Organization

Experiment Hierarchy

```
Project/
├── experiment_1/
│   ├── run_1/
│   ├── run_2/
│   └── run_3/
├── experiment_2/
│   ├── run_1/
│   └── run_2/
└── experiment_3/
    └── run_1/
```

Naming Conventions

Descriptive names: "customer_churn_rf_v1"

Team prefixes: "ds_team_sentiment_analysis"

Date stamps: "model_training_20240727"

Version tags: "baseline_v1.0"

Organization Tips

01

One experiment per major approach

02

Use tags for filtering

03

Document objectives

04

Archive old experiments

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MLflow UI Navigation

Main Sections

Experiments: View all experiments

01

Models: Access model registry

02

Runs: Detailed run information

03

Compare: Side-by-side comparisons

04

Key Features

Features

Search and filter runs

Compare parameters/metrics

Sort by metrics

View run details

Download artifacts

Collaboration Benefits

Shared experiment tracking

Team visibility

Result sharing

Knowledge transfer

Thanks

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