📘 MLflow and DagsHub

MLflow is an open-source platform for managing the ML lifecycle, including experimentation, reproducibility, and deployment.

Key Components

Component	Description
Tracking	Logs parameters, metrics, artifacts, and models during experiments.
Projects	Packaging format for reproducible runs using `MLproject` file.
Models	Standard format for packaging ML models for diverse deployment tools.
Registry	Central hub for managing model lifecycle (staging, production, archiving).

MLflow Tracking Basics

```
import mlflow

with mlflow.start_run():
    mlflow.log_param("learning_rate", 0.01)
    mlflow.log_metric("rmse", 0.78)
    mlflow.log_artifact("model.pkl")
```

Artifacts can be model files, plots, or other outputs.

🔹 MLflow UI

- Launch via: `mlflow ui`
- Default at: `http://localhost:5000`

⚙️ MLflow Project Structure

```
# MLproject
name: MyProject

conda_env: conda.yaml
```

```
entry_points:
  main:
    parameters:
      alpha: {type: float, default: 0.5}
    command: "python train.py --alpha {alpha}"
```

🏷️ MLflow Model Registry Lifecycle

1. **Register** a model version
2. Assign **Stages**: `Staging`, `Production`, `Archived`
3. Track model metadata and transitions

🛰️ DagsHub

DagsHub is a web-based platform built on top of Git, DVC, and MLflow for collaborative ML development and reproducible research.

🔹 Key Features

Feature	Description
Git & DVC	Version control for code and data via Git and DVC.
MLflow UI	Integrated MLflow tracking dashboard.
Data Lineage	Track changes and connections across code, models, and datasets.
Experiment Comparison	Visual diff of runs, metrics, parameters.

🔧 Basic Setup with DagsHub

1. Initialize Git + DVC

```
git init
dvc init
dvc remote add origin https://dagshub.com/<user>/<repo>.dvc
```

2. Add and Push Data

```
dvc add data/train.csv
```

```
git add data/train.csv.dvc .gitignore
git commit -m "Add training data"
dvc push
```

3. Integrate MLflow

- Set tracking URI:

```
mlflow.set_tracking_uri("https://dagshub.com/<user>/<repo>.mlflow")
```

- Set DagsHub credentials:

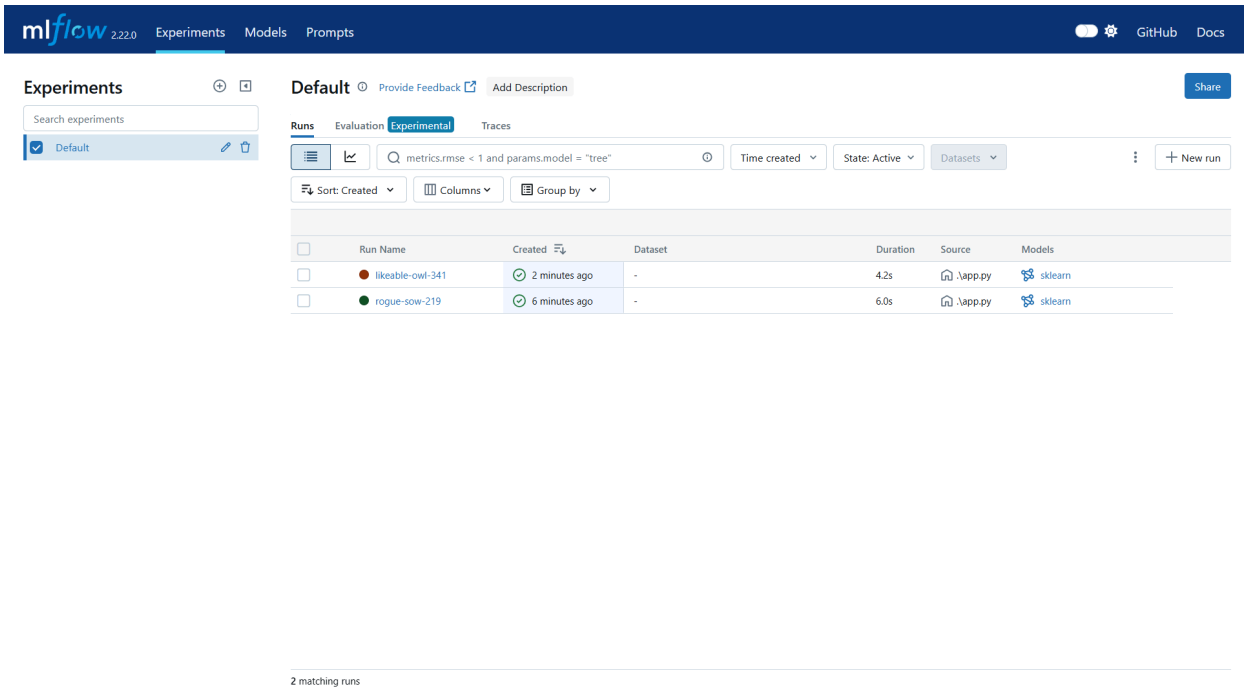
```
export MLFLOW_TRACKING_USERNAME=<your_username>
export MLFLOW_TRACKING_PASSWORD=<your_token>
```

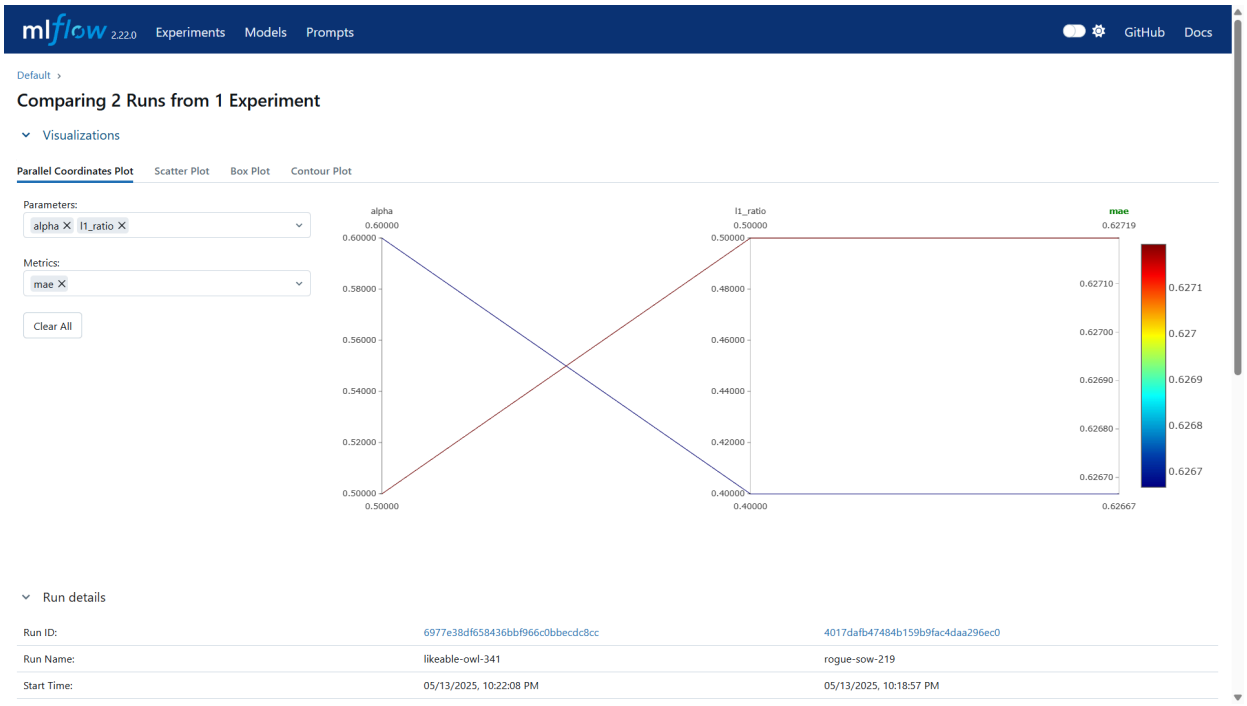
🔍 When to Use MLflow + DagsHub Together

Scenario	Tool(s)
Experiment tracking	**MLflow**
Model versioning & registry	**MLflow Registry**
Data and model version control	**DVC (via DagsHub)**
Team collaboration & review	**DagsHub UI**

📌 Tips

- Use **MLflow Autologging** for quick integration with libraries like `sklearn`, `keras`, etc.
- Use **DVC pipelines** to version and automate ML workflows.
- DagsHub is ideal for open-source and team projects needing version control + tracking.





BentoML is an open-source framework for building, packaging, and deploying machine learning models as scalable APIs or services.

🚀 Why BentoML?

Feature	Benefit
Easy API serving	Turn ML models into REST/gRPC APIs in minutes
Model packaging	Version-controlled and reproducible model storage
Multiple framework support	Works with `sklearn`, `xgboost`, `transformers`, `PyTorch`, etc.
Deployment ready	Supports Docker, Kubernetes, AWS Lambda, and more

📂 BentoML Workflow

1. Model Training (anywhere)

Train your model using your preferred framework.

```
from sklearn.ensemble import RandomForestClassifier

model = RandomForestClassifier().fit(X_train, y_train)
```

2. Save Model using BentoML

```
import bentoml

bentoml.sklearn.save_model("rf_classifier", model)
```

✅ This saves the model along with metadata and dependencies.

3. Define a Service

Create a file like `service.py`:

```
# service.py
```

```
import bentoml

from bentoml.io import NumpyNdarray


model_ref = bentoml.sklearn.get("rf_classifier:latest")

model_runner = model_ref.to_runner()


svc = bentoml.Service("rf_service", runners=[model_runner])


@svc.api(input=NumpyNdarray(), output=NumpyNdarray())

async def predict(input_data):

    return await model_runner.predict.async_run(input_data)
```

4. Run the Service Locally

```
bentoml serve service:svc
```

Runs the service at `http://localhost:3000`

5. Build a Bento (package)

```
bentoml build
```

Creates a `.bento` package in the `bentos/` directory.

6. Containerize and Deploy

- **Docker**

```
bentoml containerize rf_service:latest
```

📂 DVC

DVC is an open-source tool for **data versioning**, **experiment tracking**, and **reproducible ML pipelines**. It works alongside Git.

🔧 Why Use DVC?

Feature	Purpose
Version control for data	Like Git, but for large data files
Reproducible pipelines	Track data + code + metrics together
Remote storage	Store datasets/models in cloud/local remotes
Team collaboration	Share data without bloating the Git repo

🚀 Core Workflow

1. Initialize DVC in a Git repo

```
git init

dvc init
```

2. Track a dataset or model

```
dvc add data/train.csv

git add data/train.csv.dvc .gitignore

git commit -m "Add training data with DVC"
```

3. Push data to remote storage

```
dvc remote add -d myremote <remote-url>

dvc push
```

Supports S3, GCS, Azure, SSH, etc.

4. Pull data

```
dvc pull
```

Downloads data from remote storage (e.g., in CI or on a teammate's machine).