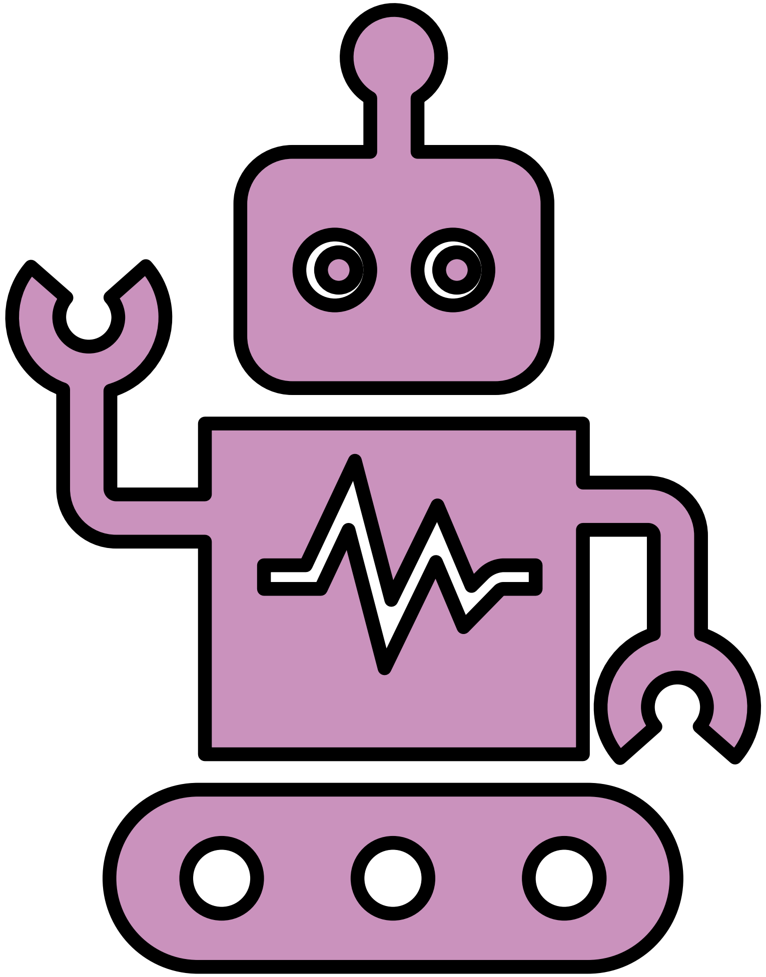
Introduction to MLflow

A Comprehensive Overview of MLflow for Machine Learning

Introduction to Mlflow:

- MLflow is a comprehensive **open-source platform** developed to address the challenges associated with the **end-to-end machine learning lifecycle**. It facilitates seamless management from the **initial experimentation phase** to the **deployment of machine learning models**.



Key Objectives:

- MLflow aims to **simplify** and enhance the machine learning development process by providing tools and components that streamline **experiment tracking**, **project packaging**, and **model deployment**. It acts as a unified platform for data scientists and machine learning engineers.

Integrations with:

PyTorch	HuggingFace	OpenAI
LangChain	Spark	Keras
TensorFlow	Prophet	scikit-learn
XGB XGBoost	LightGBM	CatBoost

Components Overview:

Tracking: Enables logging and querying of experiments, capturing essential information such as **parameters**, **metrics**, and **artifacts**.

Projects: A system for packaging code into a reproducible format, ensuring that experiments can be **easily reproduced**.

Models: Provides tools for **packaging** and **deploying** machine learning models with support for various frameworks and flavors.

Registry: A centralized repository for **managing** and **versioning** machine learning models.

Tracking:

- The tracking component in MLflow is designed to capture and log essential information during the experimentation phase of machine learning development. It ensures that every aspect of an experiment is recorded systematically for later analysis and reproducibility.

A simple example of logging:

```
import mlflow

with mlflow.start_run():
    mlflow.log_param("learning_rate", 0.01)
    mlflow.log_param("hidden_layers", 3)
    # Other code for the experiment
```

Projects:

- The Projects component in MLflow provides a standardized structure for packaging code into a format that ensures reproducibility. It encapsulates dependencies, code, and configurations, making it easy to share and reproduce experiments across different environments.

A simple example of an ‘mlproject’ File :

```yaml
name: my_project
conda_env: conda.yaml

entry_points:
  main:
    parameters:
      input_path: path
    command: "python my_script.py {input_path}"
```

Example: Running a project with the CLI

mlflow run my_project -P input_path=data.csv

Models:

- The Models component in MLflow is designed to facilitate the packaging and deployment of machine learning models. It supports various flavors, allowing flexibility in packaging models for different frameworks and libraries.

MLflow provides APIs for packaging models. For a scikit-learn model

```
import mlflow.sklearn
from sklearn.linear_model import LogisticRegression

# Train a scikit-learn model
model = LogisticRegression()
model.fit(X_train, y_train)

# Log the model with MLflow
mlflow.sklearn.log_model(model, "my_model")
```

Tracking:

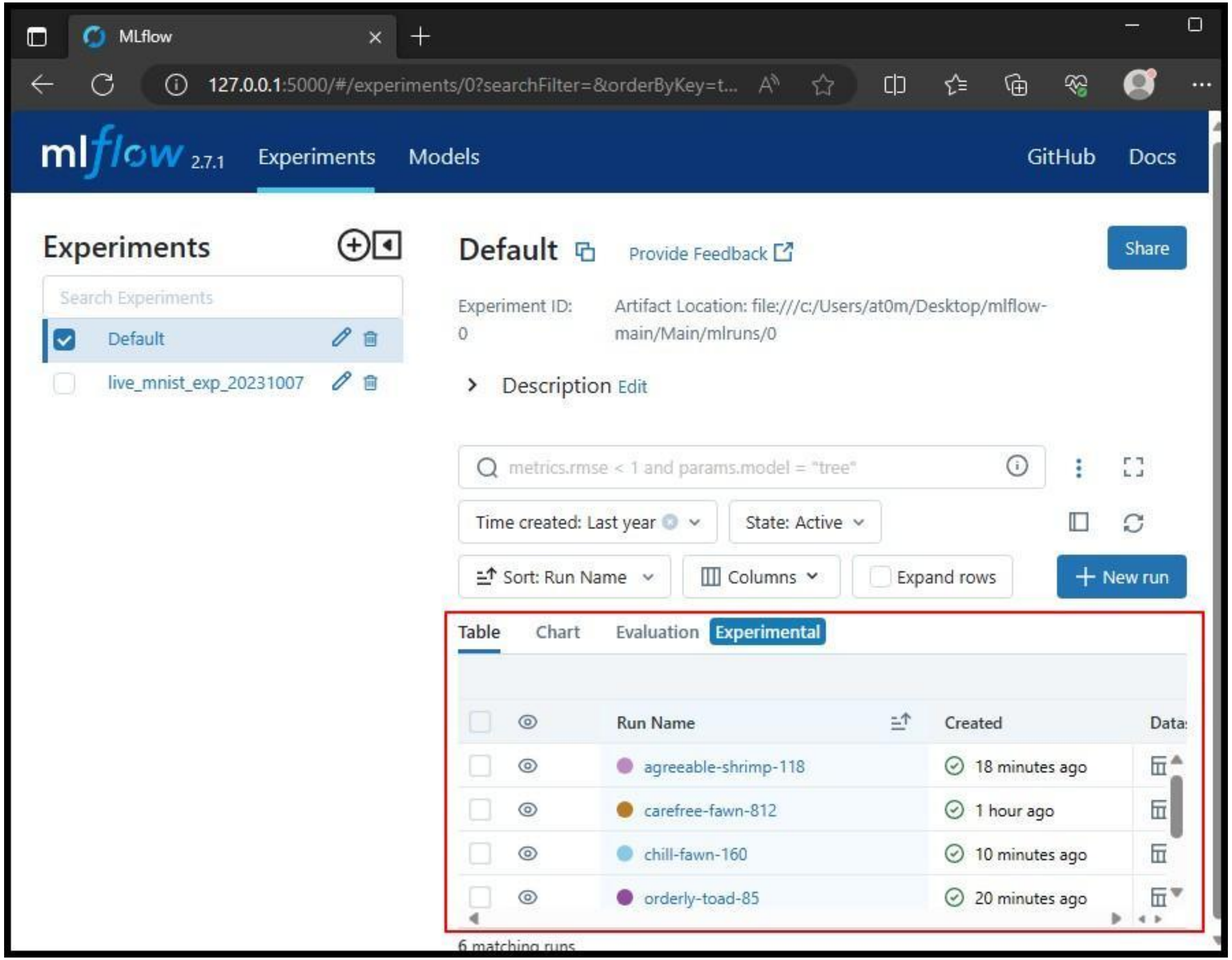
- The Registry component in MLflow serves as a centralized repository for managing and versioning machine learning models. It plays a crucial role in organizing, tracking changes, and promoting collaboration in the model development lifecycle.

A simple example of logging:

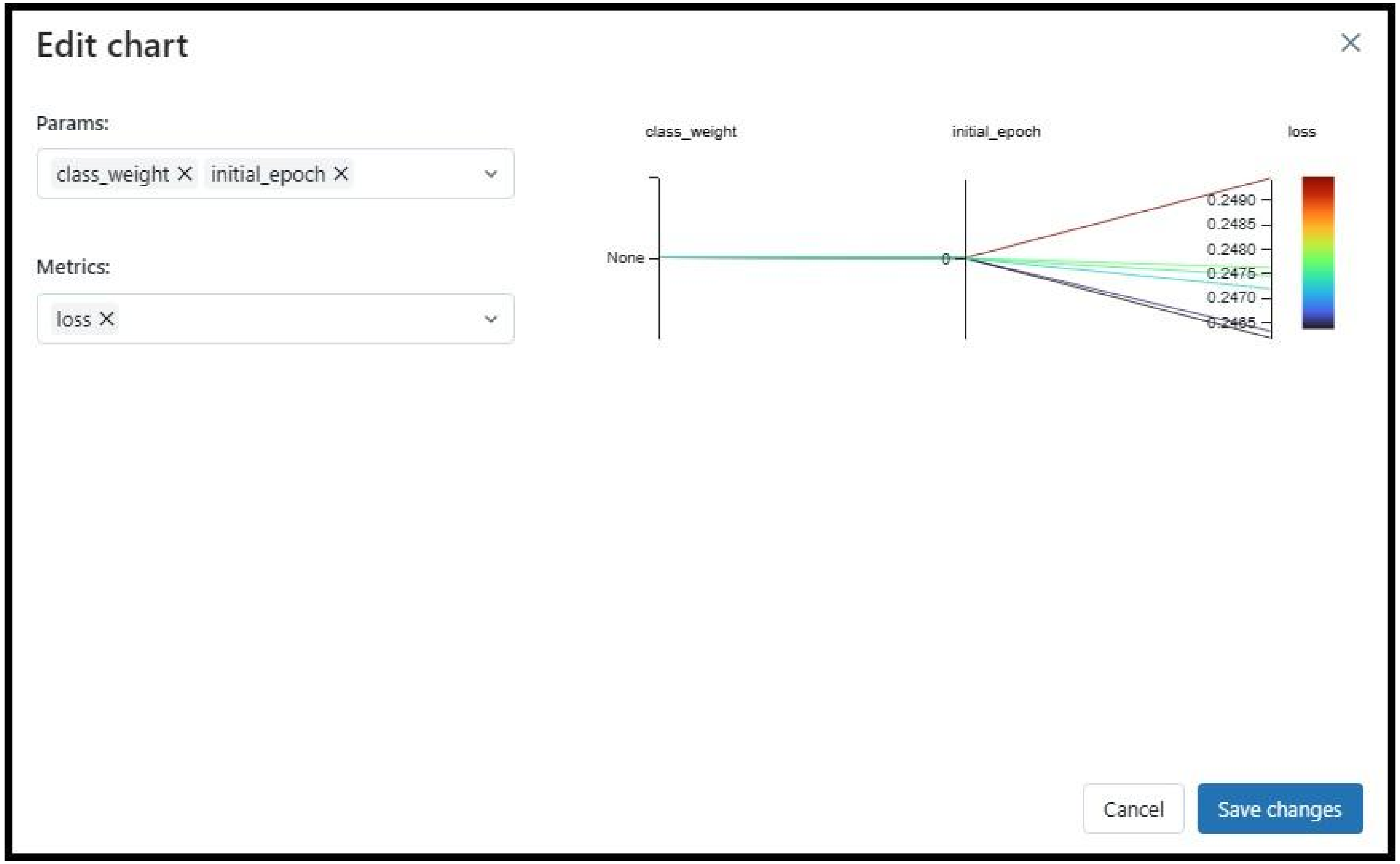
```
import mlflow.pyfunc

# Assuming 'my_model' is a registered model
mlflow.pyfunc.register(model_path="runs:/<run-id>/my_model", name="my_registered_model")
```

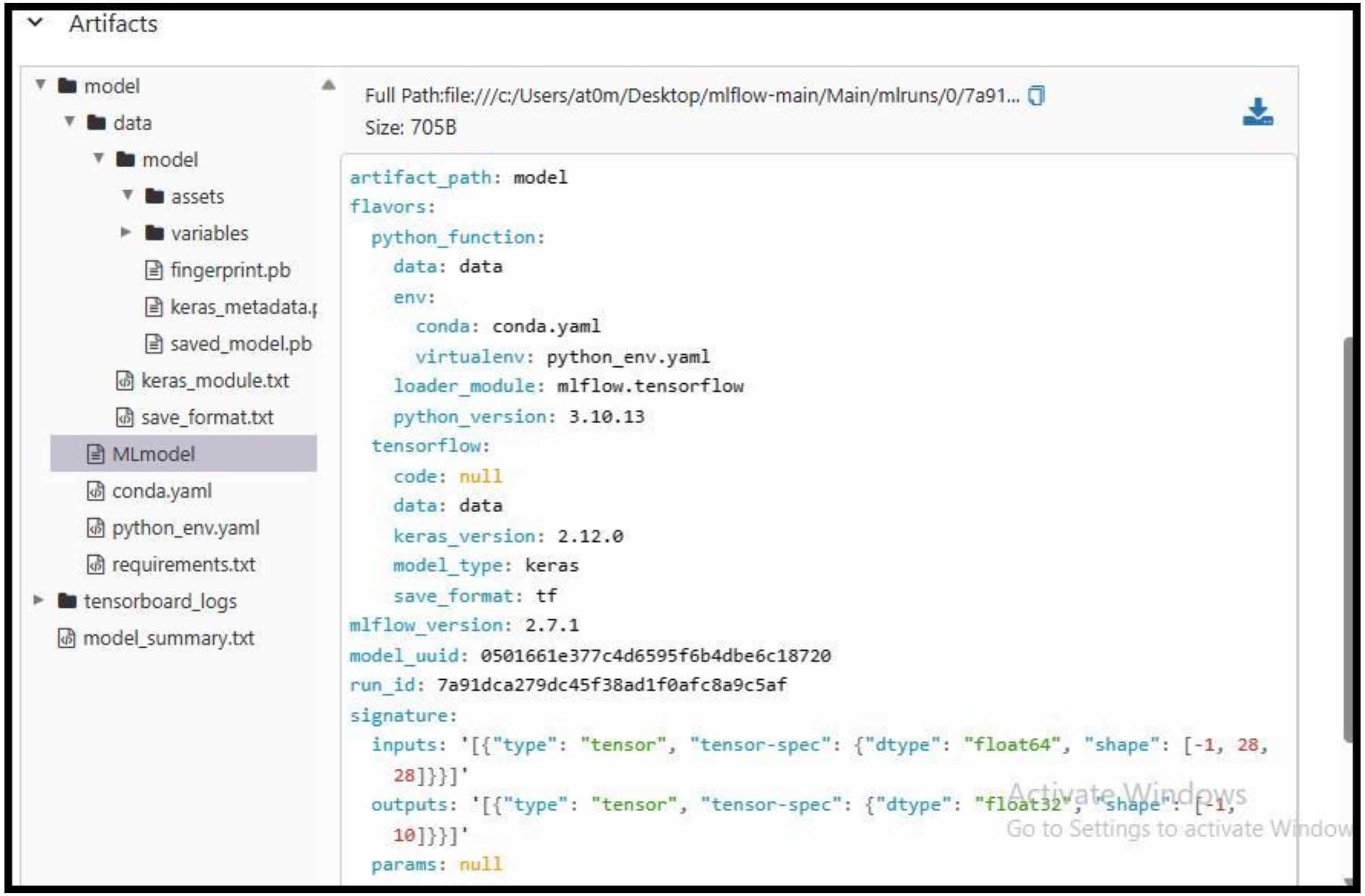
MLFLOW UI


MLflow
127.0.0.1:5000/#/experiments/0?searchFilter=&orderByKey=t...
mlflow 2.7.1
Experiments
Models
GitHub
Docs
Experiments
Search Experiments
Default
live_mnist_exp_20231007
Default
Provide Feedback
Share
Experiment ID: 0
Artifact Location: file:///c:/Users/at0m/Desktop/mlflow-main/Main/mlruns/0
Description Edit
metrics.rmse < 1 and params.model = "tree"
Time created: Last year
State: Active
Sort: Run Name
Columns
Expand rows
New run
Table
Chart
Evaluation
Experimental
Run Name
Created
agreeable-shrimp-118
18 minutes ago
carefree-fawn-812
1 hour ago
chill-fawn-160
10 minutes ago
orderly-toad-85
20 minutes ago
6 matching runs

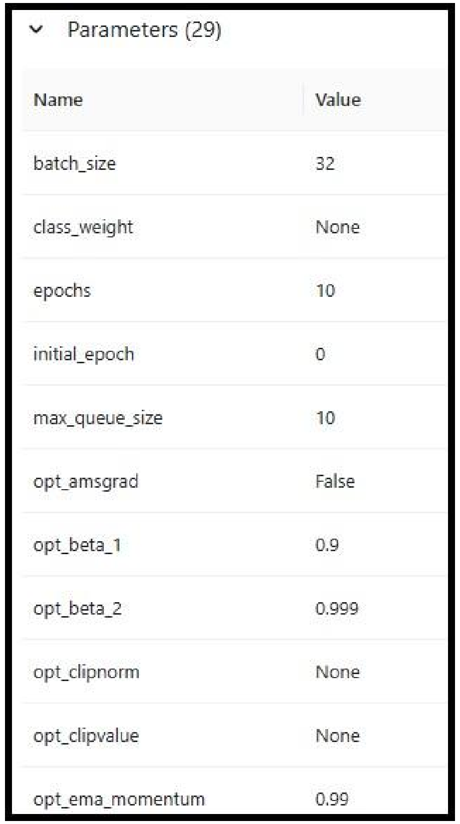
Visualize Data Easily



Organized Assets Easily

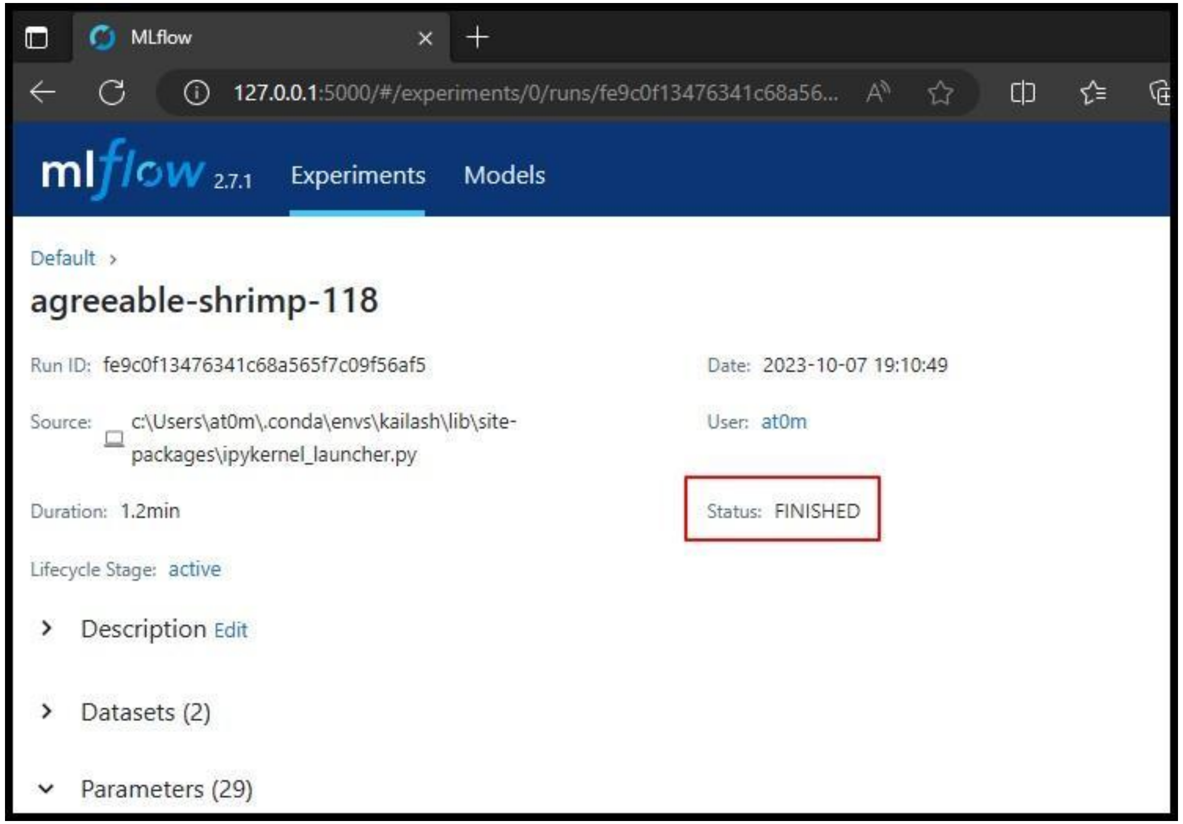


No Need to Manually LOG Everything



Parameters (29)

Name	Value
batch_size	32
class_weight	None
epochs	10
initial_epoch	0
max_queue_size	10
opt_amsgrad	False
opt_beta_1	0.9
opt_beta_2	0.999
opt_clipnorm	None
opt_clipvalue	None
opt_ema_momentum	0.99



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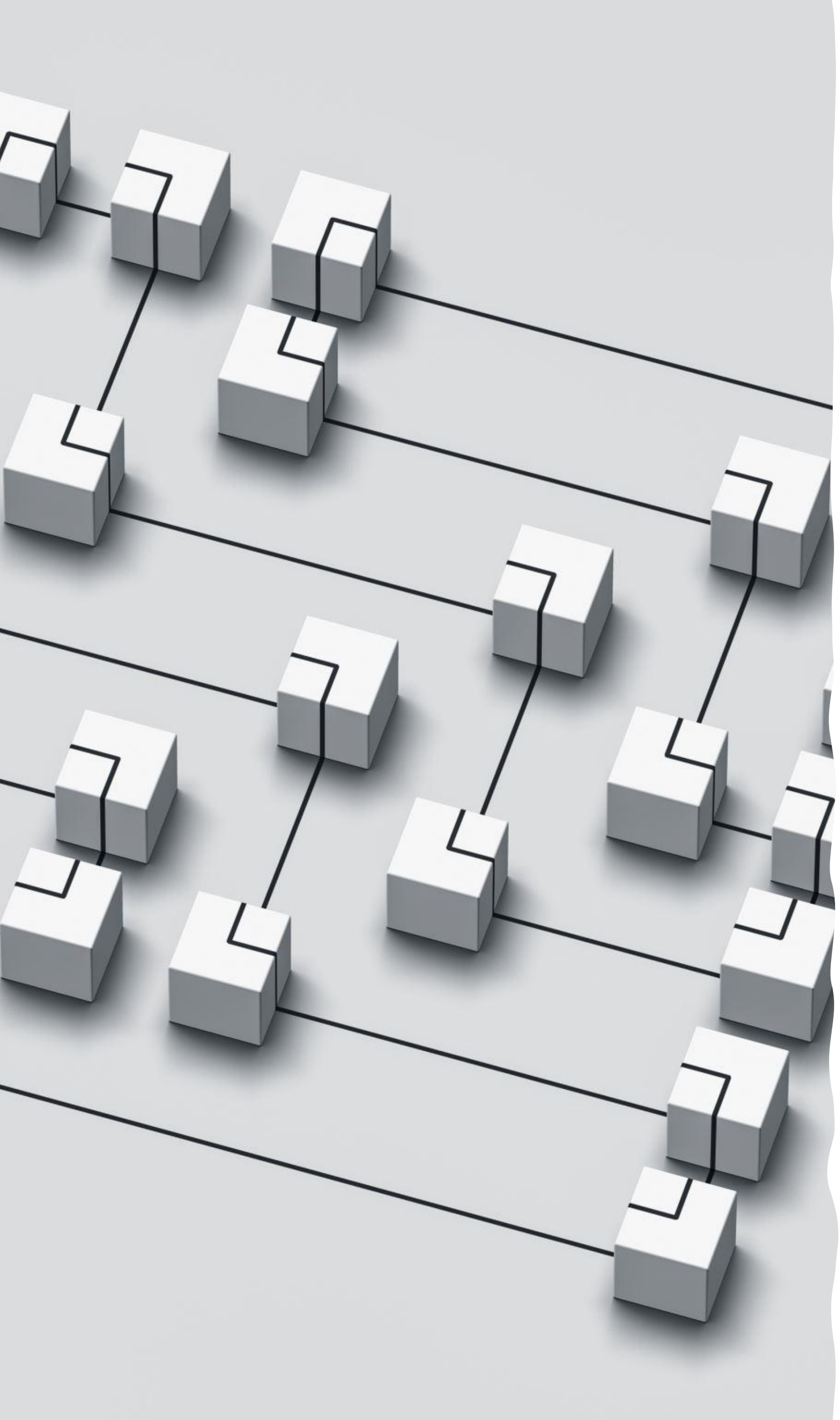
- https://drive.google.com/file/d/1lk9a_8AplqdyX53ZMfryD68-B5DRSSDs/view?usp=drive_link



Advantages of Mlflow:

- **Ease of Experiment Tracking:**
  - Captures parameters, metrics, artifacts, and source code.
  - Enables easy comparison of multiple experiments.
- **Reproducibility:**
  - Records the environment, dependencies, and versioning to ensure reproducibility.
- **Model Packaging and Deployment:**
  - Simplifies packaging and sharing of models.
  - Supports deployment to a variety of platforms (cloud, on-premises, edge devices).

Best Practices and Tips

Version Control for Code and Data	Comprehensive Documentation	Environment Reproducibility	Model Registry Naming Conventions
Regular Model Retraining	Security Measures	Continuous Integration (CI) for MLflow Projects	Regularly Clean Up Unused Experiments

Conclusion

- Recap of Key Points
- Empowering the Machine Learning Lifecycle
- Enhancing Collaboration and Reproducibility
- Flexibility in Deployment