







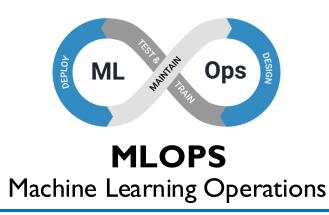


Video I Experiment/Tracking

Video 2 Orchestration

Video 3 Deployment

Video 4 Monitoring











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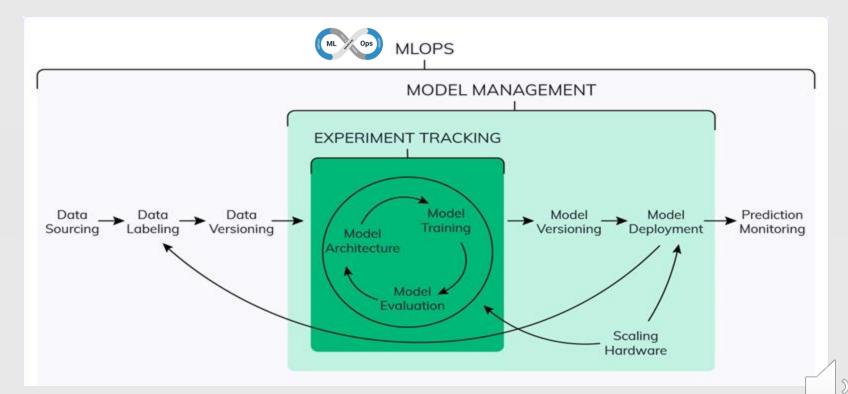
MLOPS TARGET (ML) Ops)

 Unifies ML development & operations - Ensures reliable, scalable, and reproducible model lifecycle

2. Key Focus:

- a. Automation of training, deployment, monitoring
- b. CI/CD for ML pipelines
- c. Governance & Compliance (versioning, auditing)

MACHINE LEARNING LIFECYCLE



MLOPS MATURITY MODEL FROM MICROSOFT

Level 0: No MLOPS

- Manual, ad-hoc training & deployment
- Teams siloed, no versioning or monitoring

Level I: DevOps—but no MLOPS

- Basic CI/CD for apps
- Models still trained & deployed manually

Level 2: Automated Training

- Reproducible experiments
- Automated pipelines for data prep & training

Level 3: Automated Model Deployment

- CI/CD for models
- Testing, monitoring & A/B deployments

Level 4: Full MLOPS Automated Operations

- End-to-end automation (train \rightarrow deploy \rightarrow monitor \rightarrow retrain)
- Continuous feedback loop, reliable & scalable ML in production



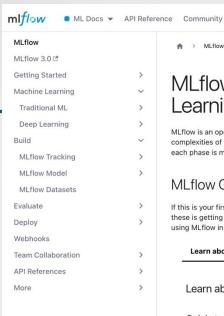
STREAMLINING THE MACHINE LEARNING LIFECYCLE

WHAT IS mlflow?

- I. Open-source platform for managing the ML lifecycle.
- 2. Facilitates experiment tracking, model versioning, and deployment.
- 3. Supports multiple ML frameworks and libraries.

https://mlflow.org/docs/latest/ml/





> MLflow

MLflow: A Tool for Managing the Machine Learning Lifecycle

MLflow is an open-source platform, purpose-built to assist machine learning practitioners and teams in handling the complexities of the machine learning process. MLflow focuses on the full lifecycle for machine learning projects, ensuring that each phase is manageable, traceable, and reproducible.

MLflow Getting Started Resources

If this is your first time exploring MLflow, the tutorials and guides here are a great place to start. The emphasis in each of these is getting you up to speed as quickly as possible with the basic functionality, terms, APIs, and general best practices of using MLflow in order to enhance your learning in area-specific guides and tutorials.

MLflow Models Introduction Learn about MLflow MLflow Basics Traditional ML Deep Learning

Learn about the core components of MLflow

Quickstarts

Get Started with MLflow in our 5-minute tutorial

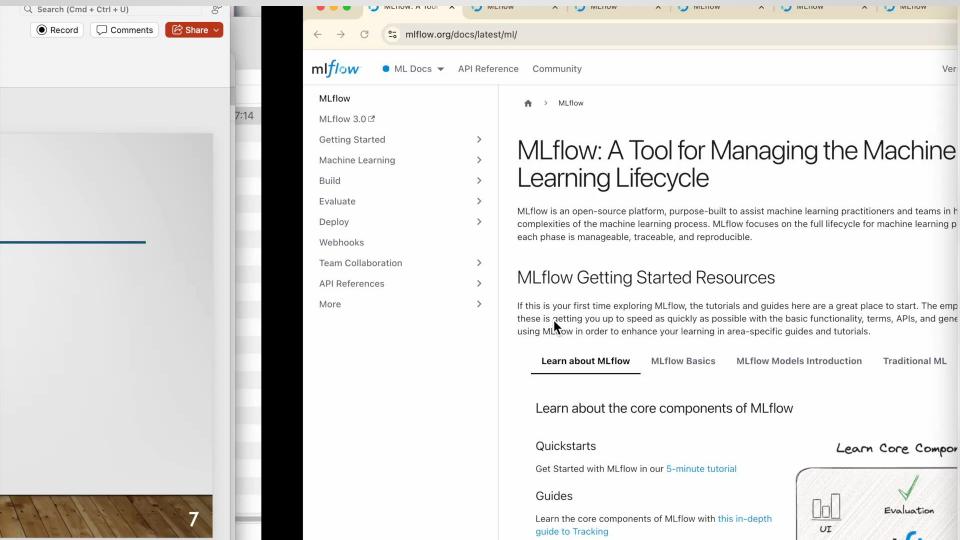
Guides

Learn the core components of MLflow with this in-depth guide to Tracking

Learn Core Components

Version: 3.4.0rc0 (latest) ▼





mlflow POPULAR COMPONENTS

1.Tracking

- Log and query experiments.
- Record parameters, metrics, and artifacts.
- Compare and visualize results.

2. Models

- Log and store models in various formats.
- Serve models for inference.

3. Model Registry

- Centralized store for managing model versions.
- Track model lineage and stages (e.g., staging, production).

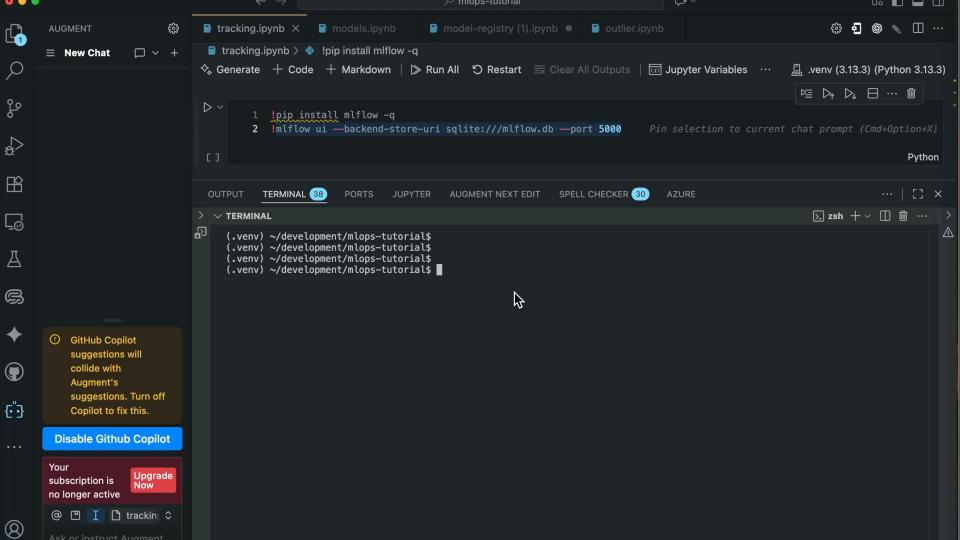
GETTING STARTED WITH mlflow

- I. Installation:

 pip install mlflow
- 2. Run on local system: mlflow ui –backend-store-uri sqlite://mlflow.db –port 5000
- 3. Run on server:

 mlflow server -h 0.0.0.0 -p 5000 --backend-store-uri

 postgresql://DB_USER:DB_PASSWORD@DB_ENDPOINT:5432/DB_NAME --defaultartifact-root s3://S3 BUCKET NAME



I. MLFLOW TRACKING

• Purpose:

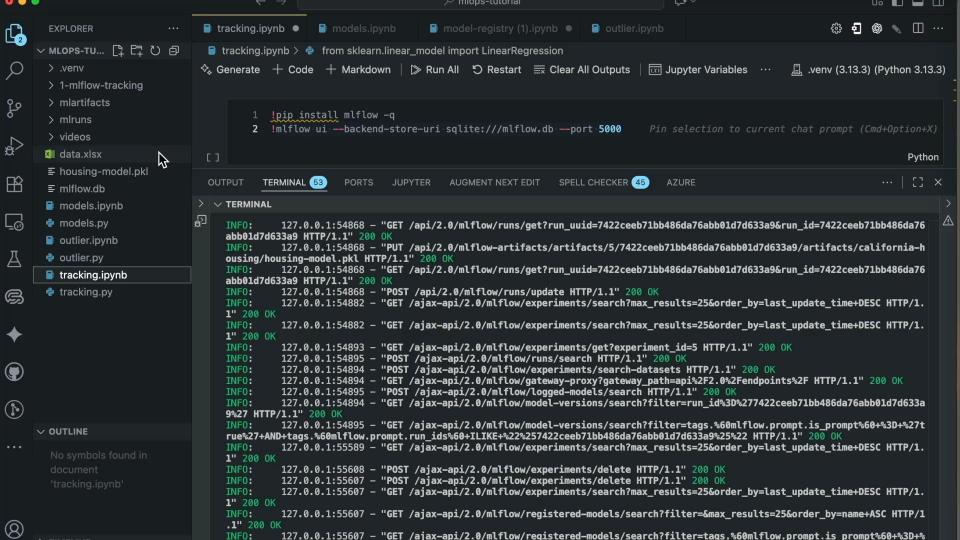
 Monitor and compare machine learning experiments.

• Features:

- Log parameters, metrics, and artifacts.
- Organize experiments into runs.
- Visualize performance over time.

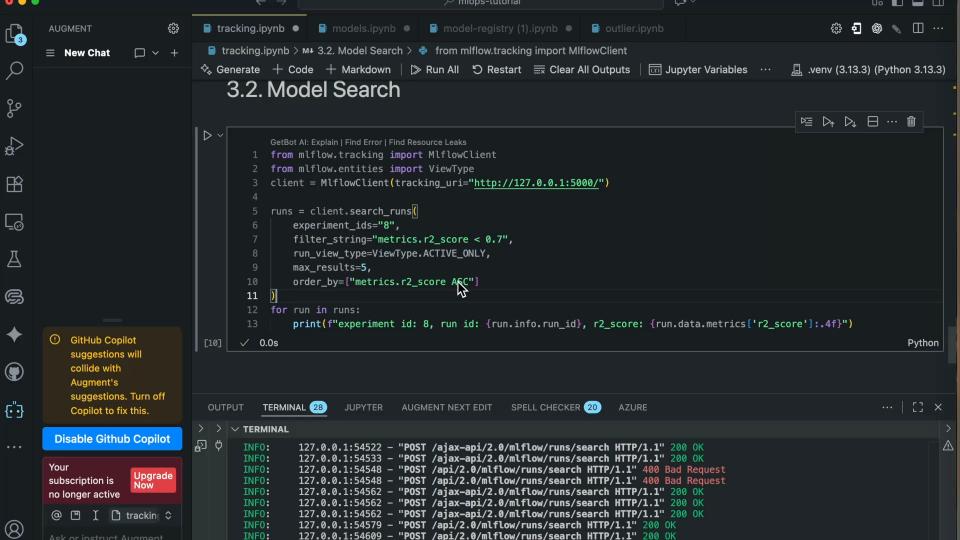
BASIC FUNCTIONS IN PYTHON PACKAGE

- I. Import the package: import mlflow
- 2. Set mlflow server uri: mlflow.set_tracking_uri()
- Set experiment unique name: mlflow.set_experiment()
- 4. Set the scope of MLflow tracking operation: with mlflow.start_run()
 - a. Set tag (arbitrary twisted variable- key-value pair): mlflow.set_tag()
 - b. Set training and model parameters (epoch, ...): mlflow.log_param()
 - c. Set a group of training and model parameters (epoch, ...): mlflow.log_params()
 - d. Log metrics name and value: mlflow.log_metric()
 - e. Save artifact (model files, dataset, ...): mlflow.log_artifact()



RUN SEARCH

```
from mlflow.tracking import MlflowClient
   from mlflow.entities import View Type
   mlflow tracking uri = "http://127.0.0.1:5000/"
   client = MlflowClient(tracking uri= mlflow tracking uri)
   runs = client.search_runs(
      experiment ids='3',
6.
      filter string="metrics.mean squared error < 0.6",
8.
      run view type=ViewType.ACTIVE ONLY,
9.
      max results=5,
      order by=["metrics.mean squared error ASC"]
10.
H.)
12. for run in runs:
      print(f"run id: {run.info.run id}, rmse: {run.data.metrics['mean squared error']:.4f}")
```



2. MLFLOW MODELS

• Purpose:

 Manage and serve machine learning models.

• Features:

- Log models in different formats (e.g., TensorFlow, PyTorch).
- Serve models via REST APIs.
- Deploy models to various platforms.

MLFLOW MODELS WITH ML PYTHON PACKAGES

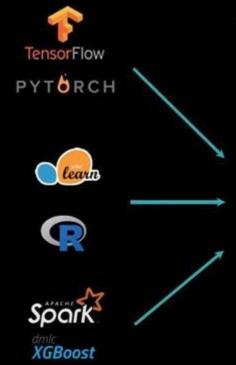
I. Logging models:

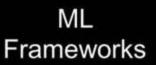
```
mlflow.<framework>.log_model(our_model, name="mlflow_model_path")
```

2. Loading models:

```
model_uri = 'models:/{model_id}'
Load model = mlflow.pyfunc.load model(model uri )
```

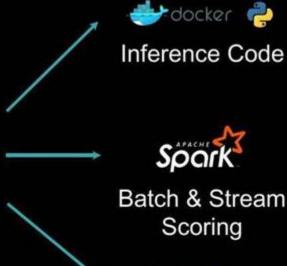
MLflow Models







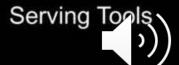
Standard for ML models

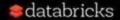






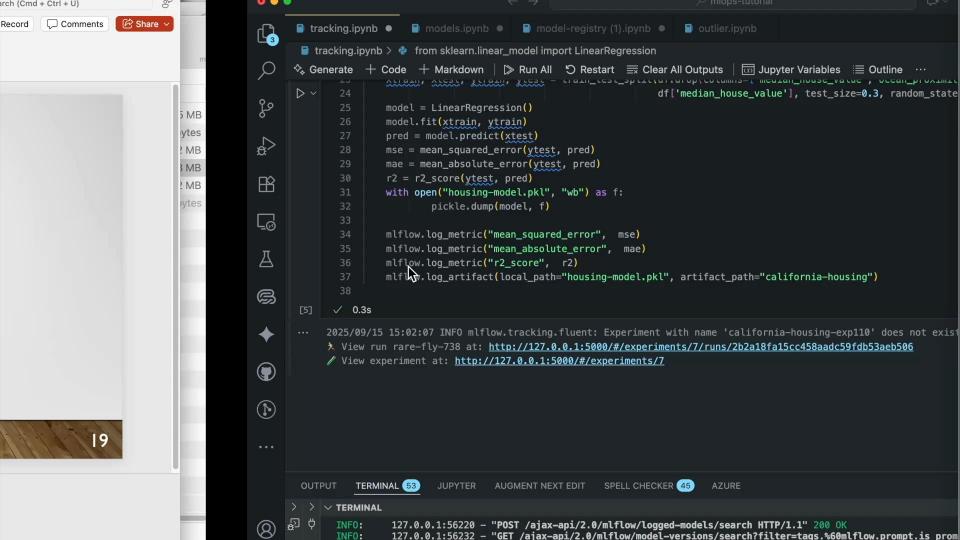






MLFLOW MODELS WITH SKLEARN (EXAMPLE)

- mlflow.sklearn.log_model(model, name="housing_linear_regression_2")
 Mlflow_model_path
 - a. MLmodel
 - b. conda .yaml
 - c. model.pkl
 - d. python_env.yaml
 - e. requirements.txt
- 2. modelid = "m-b0af883a2203425789159bba8937beef"
- 3. model_uri = 'models:/{}'.format(modelid)
- 4. load_model = mlflow.pyfunc.load_model(model_uri)



3. MLFLOW MODEL REGISTRY

• Purpose:

 Centralized management of model lifecycle.

• Features:

- Version control for models.
- Track model lineage and metadata.
- Transition models between stages (e.g., from development to production)

PROBLEM: WITHOUT A MODEL REGISTRY

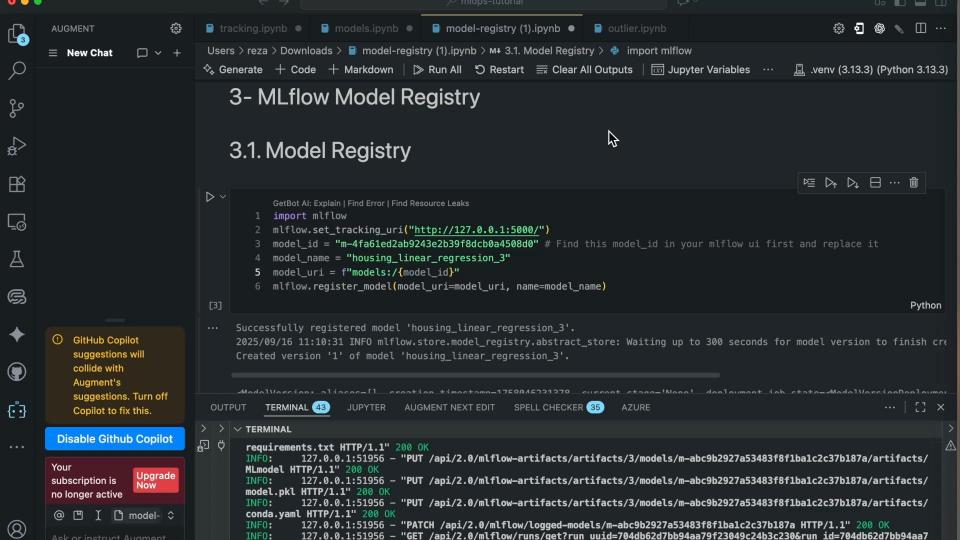
- 1. Deploying new ML models often requires messy back-and-forth emails.
- 2. Hard to track:
 - a. What changed between versions
 - b. Preprocessing steps, dependencies, hyperparameters
 - c. Rollback to previous models during incidents
- 3. Leads to inefficiency & risk of losing reproducibility.

MODEL REGISTRY WORKFLOW

- 1. Experiment Tracking: log parameters, metrics, artifacts, models.
- 2. Register Models: select best performing ones.
- 3. Assign Stages:
 - a. Staging: under review/testing.
 - b. Production: live model.
 - c. Archived: deprecated models (can rollback).
- 4. Model Metadata: size, training time, error metrics, dependencies.

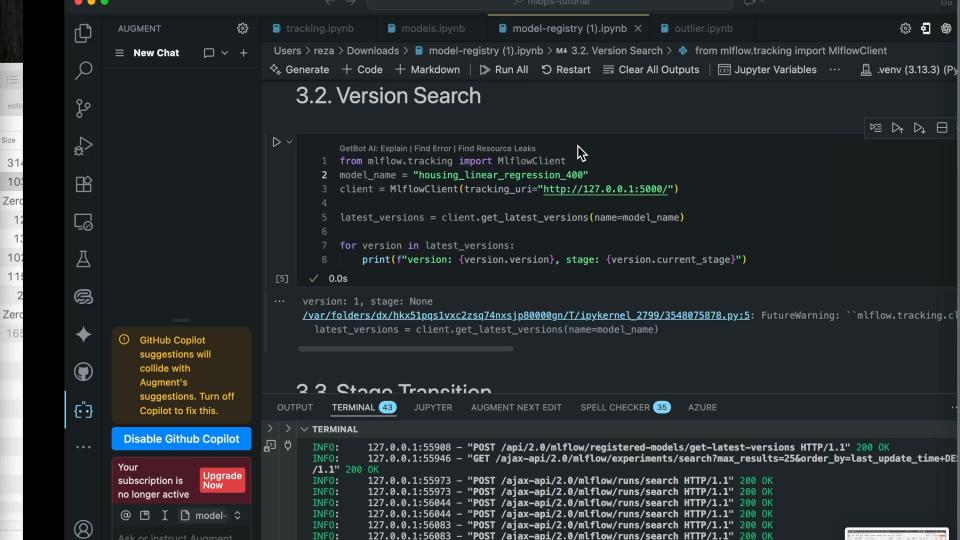
MODELS REGISTRY WITH PYTHON PACKAGES

- I. model id = "m-609655c524b342f4ae1fe947af81945e"
- 2. model name = "test7"
- 3. model uri = f'models:/{model id}"
- 4. mlflow.register model(model_uri=model_uri, name=model_name)



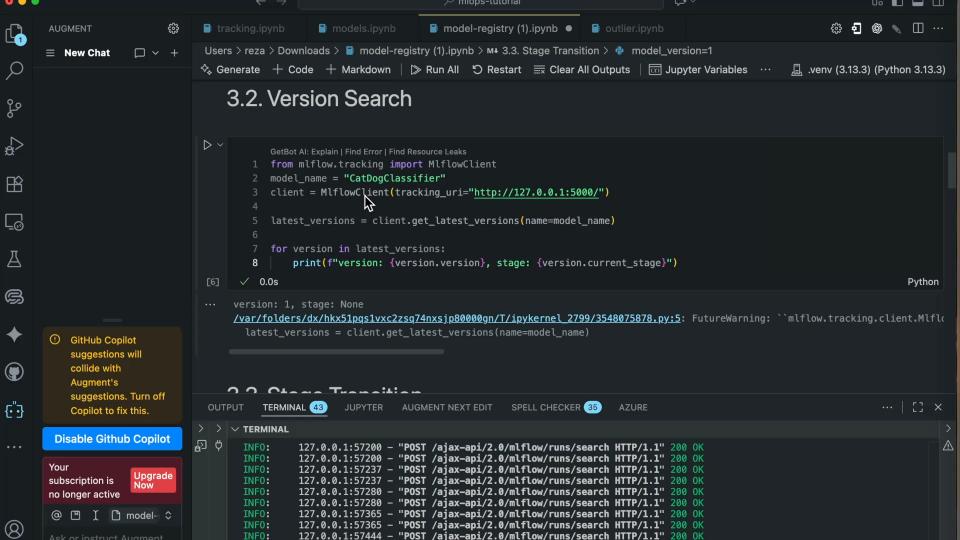
VERSION SEARCH

- I. from mlflow.tracking import MlflowClient
- 2. model_name = "housing_linear_regression_400"
- 3. client = MlflowClient(tracking_uri="http://127.0.0.1:5000/")
- 4. latest_versions = client.get_latest_versions(name=model_name)
- 5. for version in latest versions:
- 6. print(f"version: {version.version}, stage: {version.current_stage}")



STAGETRANSITION (NONE -> STAGING -> PRODUCTION -> ARCHIVED)

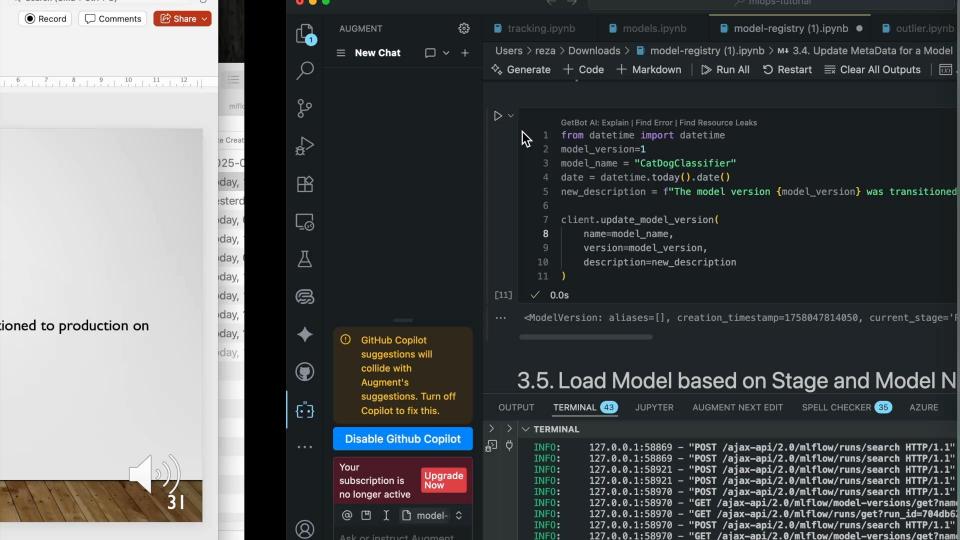
```
    model_version = I
    new_stage = "Staging"
    model_name = "housing_linear_regression_400"
    client.transition_model_version_stage(
        name=model_name,
        version=model_version,
        stage=new_stage,
        archive_existing_versions=False
```



UPDATE METADATA FOR A MODEL

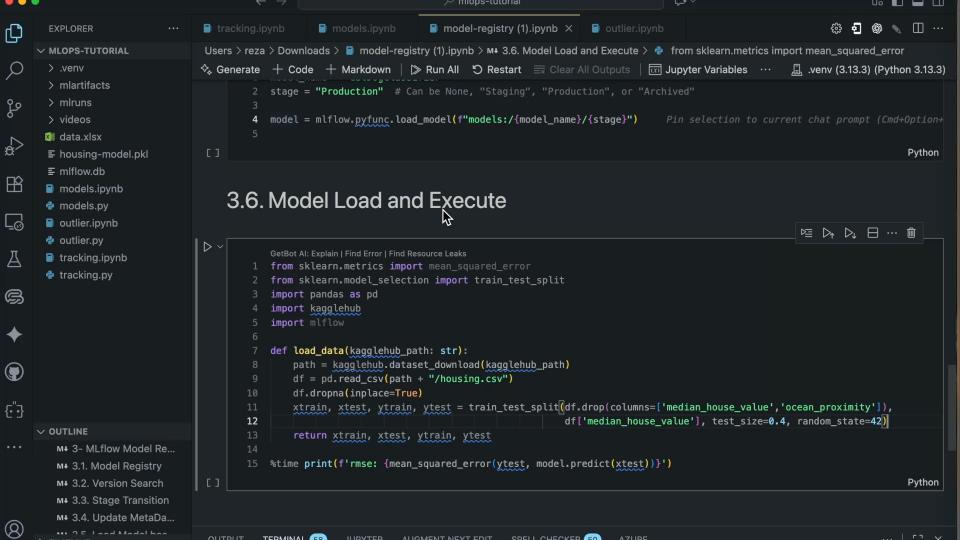
- I. from datetime import datetime
- model_version=I
- model name = "housing linear regression 400"
- 4. date = datetime.today().date()
- 5. new_description = f"The model version {model_version} was transitioned to production on {date}"
- 6. client.update_model_version(

```
name=model_name,
version=model_version,
description=new_description
)
```



LOAD MODEL BASED ON STAGE AND MODEL NAME

- I. model_name = "housing_linear_regression_400"
- 2. stage = "Production"
- 3. model = mlflow.pyfunc.load_model(f"models:/{model_name}/{stage}")





THANK YOU! ANY QUESTIONS?

- I-Tracking
- 2- Models
- 3- Model Registry
- a- set experiment
- b- search runs
- c- log models
- d- load model
- e- register model
- f- search model
- g- set model stage
- h- update model metadata
- i- load and execute a model