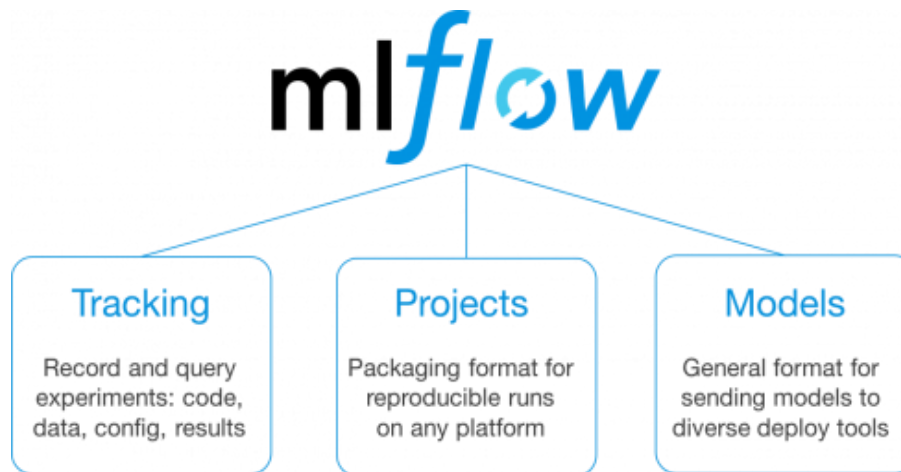


Experiment Tracking and Model Management

In this project, we create an experiment tracking our dataset i.e diamond.csv using ML Flow.

ML Flow



What is MLFlow?

MLFlow is a framework that supports the machine learning lifecycle. This means that it has components to monitor your model during training and running, the ability to store models, load the model in production code, and create a pipeline.

MLFlow Tracking—

Tracking is maybe the most interesting feature of the framework. It allows you to create an extensive logging framework around your model. You can define custom metrics so that after a run you can compare the output to previous runs.

MLFlow Projects—

This feature allows you to create a pipeline if you so desire. This feature uses its own template to define how you want to run the model on a cloud environment. As most companies have a way to run code in production this feature might be of less interest to you.

MLFlow Models—

Finally we have the Models feature. An MLFlow Model is a standard format for packaging machine learning models that can be used in a variety of downstream tools — for example, real-time serving through a REST API or batch inference on Apache Spark.

Command to Install MLFlow—

```
pip install mlflow
mlflow ui --backend-store-uri sqlite:///mlflow.db
```

How to implement MLFlow in our application—

Step-1

```
import mlflow
```

Step 2 - Set the tracker and experiment

```
mlflow.set_tracking_uri(DATABASE_URI)
mlflow.set_experiment("EXPERIMENT_NAME")
```

Step 3 - Start a experiment run

```
with mlflow.start_run():
```

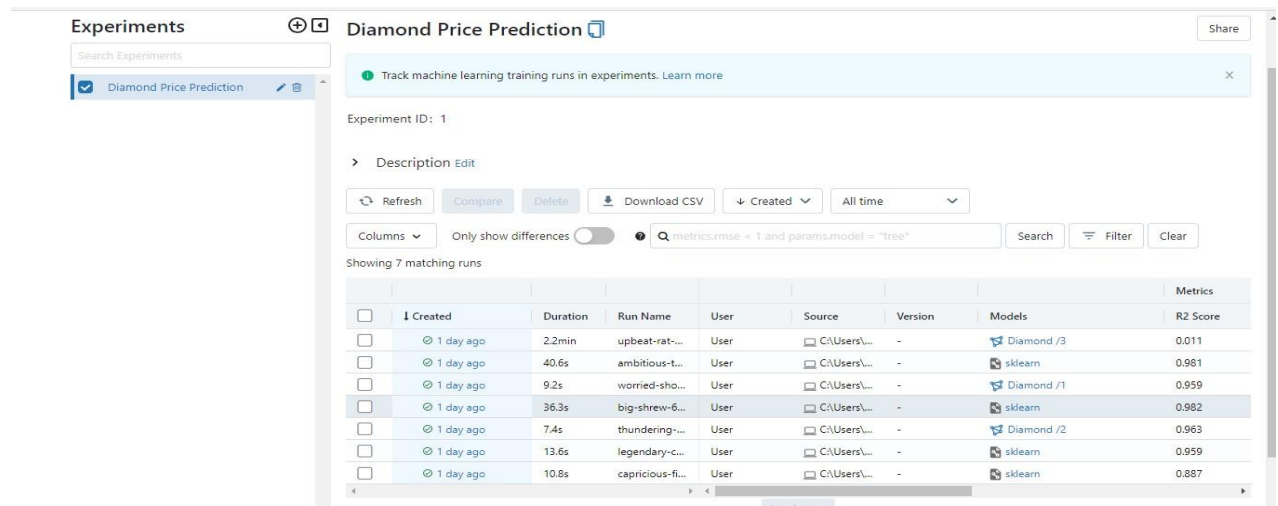
Step 4 - Logging the metadata

```
mlflow.set_tag(KEY, VALUE)
mlflow.log_param(KEY, VALUE) mlflow.log_metric(KEY, VALUE)
```

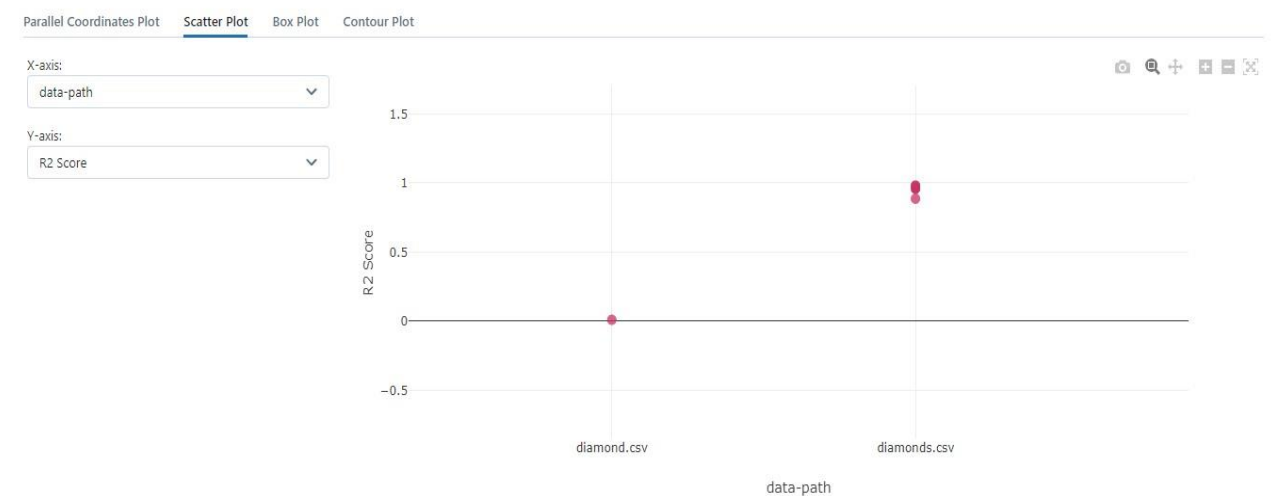
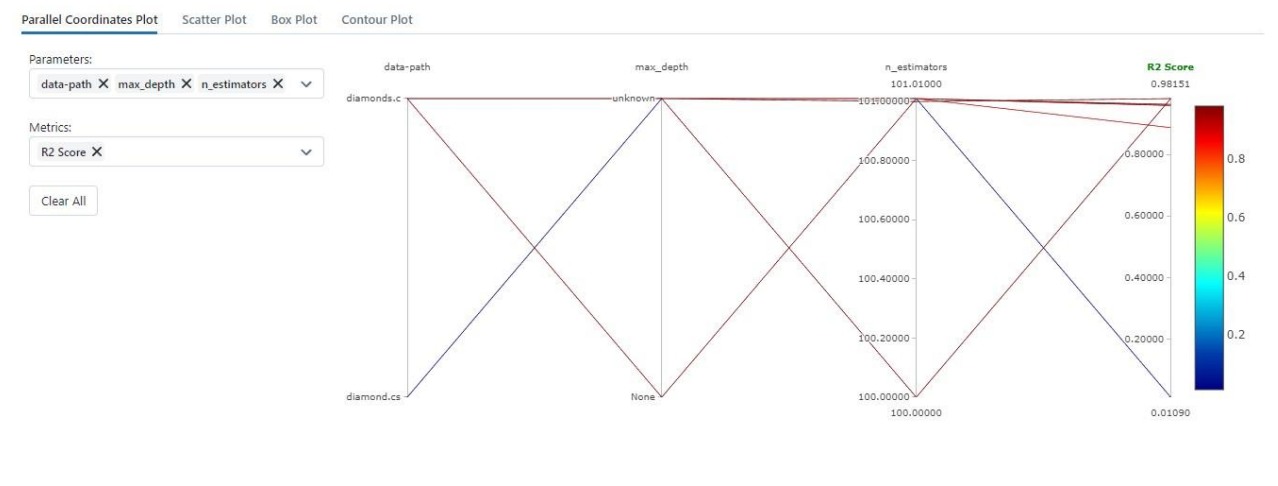
Step 5 - Logging the model and other files (2 ways)

```
Way 1 - mlflow.<FRAMEWORK>.log_model(MODEL_OBJECT, artifact_path="PATH")
Way 2 - mlflow.log_artifact(LOCAL_PATH, artifact_path="PATH")
```

MLFlow Interface Experiment Tracking—



Comparison Graph among different models—



MLFlow Interface for Model Management—



The screenshot shows the MLFlow Model Management interface. At the top, there are tabs for 'All', 'Active 2', and 'Compare'. Below the tabs is a table with columns: 'Version', 'Registered at', 'Created by', 'Stage', and 'Description'. There are three rows of model versions, each with a checkbox, a status icon (a green checkmark), and a version number. The 'Stage' column shows 'Archived', 'Production', and 'Staging' for the three versions respectively. At the bottom right, there are navigation buttons: '<', '1', and '>'.

<input type="checkbox"/>	Version	Registered at	Created by	Stage	Description
<input type="checkbox"/>	Version 3	2022-09-23 20:28:46		Archived	
<input type="checkbox"/>	Version 2	2022-09-23 20:16:51		Production	
<input type="checkbox"/>	Version 1	2022-09-23 20:16:01		Staging	

Pipeline using Workflow Orchestration tool i.e. Prefect

Install Prefect On Machine—

```
pip install prefect
```

Run Prefect—

```
prefect orion start
```

What is prefect?

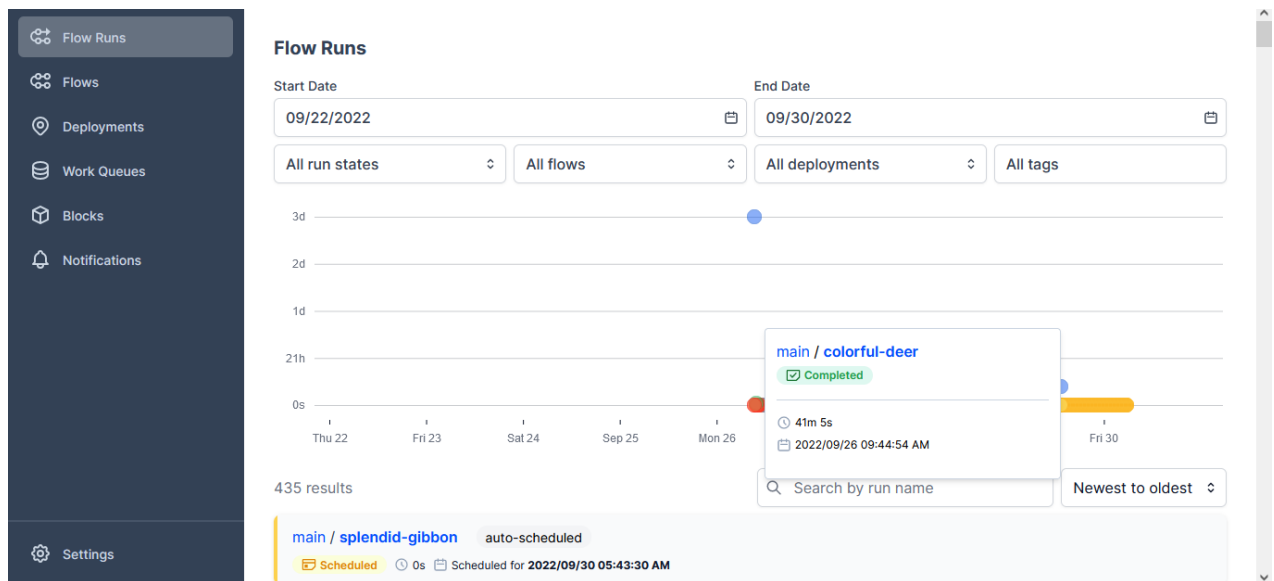
Up to this point, we've demonstrated running Prefect flows and tasks in a local environment using the ephemeral Prefect Orion API. As you've seen, it's possible to run flexible, sophisticated workflows in this way without any further configuration.

Many users find running flows locally is useful for development, testing, and one-off or occasional workflow execution.

Where you begin leveraging the full power of Prefect is when you begin using Prefect for flow coordination and orchestration — building, running, and monitoring your workflows at scale.

Orchestration with Prefect helps you schedule and deploy workflows that run in the environments best suited to their execution. Orchestration helps you prevent and recover from failures, and view and manage the status of workflows, making your workflow:

Prefect Home Page---



Workflow Pipeline—

