

SCREENSHOT
Document
for
UpGrad's Assignment
Submission

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Contents

Airflow Main UI Page	4
Initial run of Lead_Scoring_Data_Engineering_Pipeline	4
Initial run of Lead_scoring_training_pipeline	6
Initial run of Lead_scoring_inference_pipeline	7
Next run of Lead_Scoring_Data_Engineering_Pipeline	9
Next run of Lead_scoring_inference_pipeline	10
MLFlow of Baseline_model_exp01	12
MLFlow of Baseline_model_exp02	13
MLFlow of Lead_scoring_mlflow_production	14
Pytest of Data Pipeline	19

Table of Figures

Figure 1: Airflow Main UI Page.....	4
Figure 2: Grid view of Lead_Scoring_Data_Engineering_Pipeline	5
Figure 3: Graph view of Lead_Scoring_Data_Engineering_Pipeline	5
Figure 4: Grid view of Lead_scoring_training_pipeline	6
Figure 5: Graph view of Lead_scoring_training_pipeline	7
Figure 6: Grid view of Lead_scoring_inference_pipeline.....	8
Figure 7: Graph view of Lead_scoring_inference_pipeline.....	8
Figure 8: Grid view of Lead_Scoring_Data_Engineering_Pipeline	9
Figure 9: Graph view of Lead_Scoring_Data_Engineering_Pipeline	10
Figure 10: Grid view of Lead_scoring_inference_pipeline.....	11
Figure 11: Graph view of Lead_scoring_inference_pipeline.....	12
Figure 12: Main MLFlow UI of Baseline_model_exp01	12
Figure 13: MLFlow Artifacts of Baseline_model_exp01.....	13
Figure 14: Main MLFlow UI of Baseline_model_exp02	13
Figure 15: MLFlow Artifacts of Baseline_model_exp02.....	14
Figure 16: Main MLFlow UI of Lead_scoring_mlflow_production.....	15
Figure 17: MLFlow Artifacts of Version 1 model	16
Figure 18: MLFlow Artifacts of Version 2 model	17
Figure 19: MLFlow Artifacts of Version 3 model	19
Figure 20: Version 3 model registered as Production Stage	19
Figure 21: Pytest Test Results.....	19

Airflow Main UI Page

This is the main Airflow UI page that contains all the registered DAGs. We can see our 3 DAGs:

- Lead_Scoring_Data_Engineering_Pipeline
- Lead_scoring_training_pipeline
- Lead_scoring_inference_pipeline

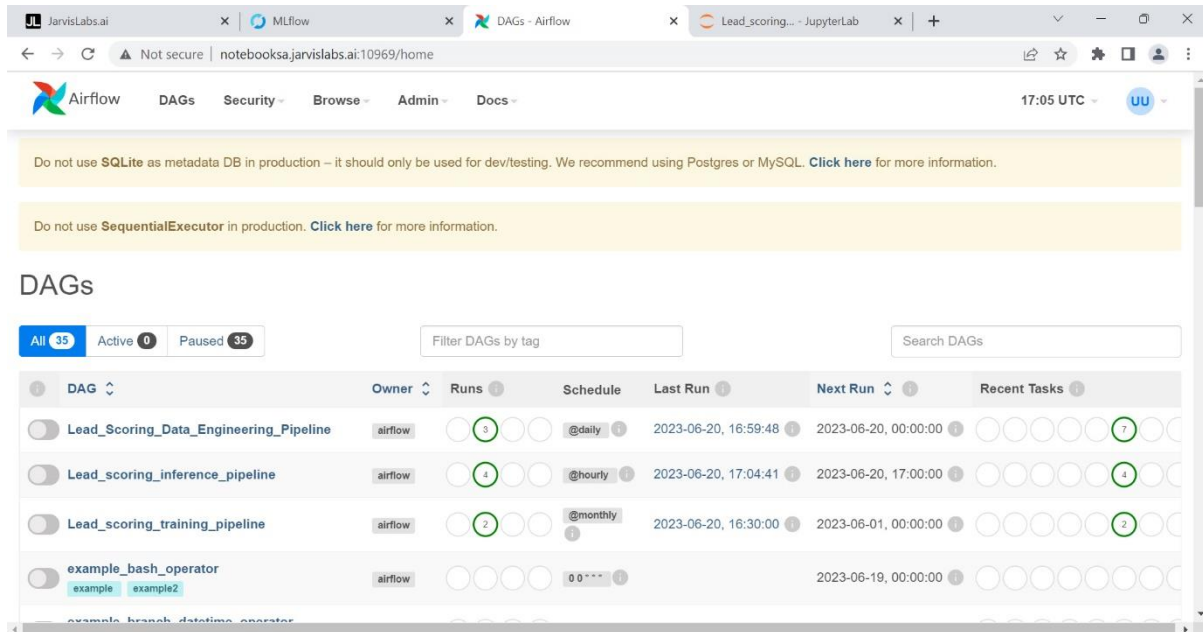


Figure 1: Airflow Main UI Page

Initial run of Lead_Scoring_Data_Engineering_Pipeline

We have triggered manual run of Lead_Scoring_Data_Engineering_Pipeline for data engineering and cleaning data.

Both manual and scheduled runs can be seen in picture. Manual runs have white coloured arrow on top of green bars in Grid view.

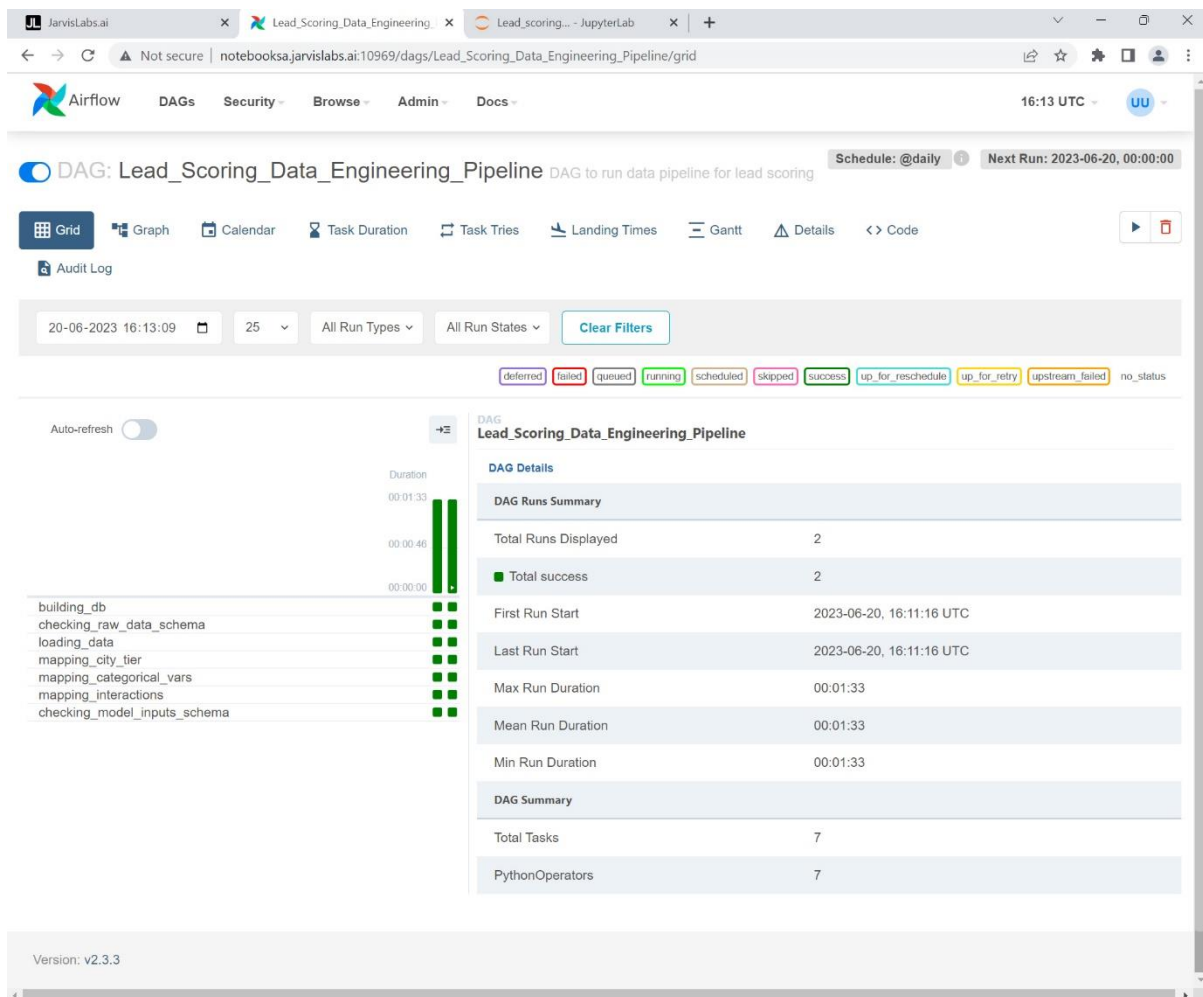


Figure 2: Grid view of Lead_Scoring_Data_Engineering_Pipeline

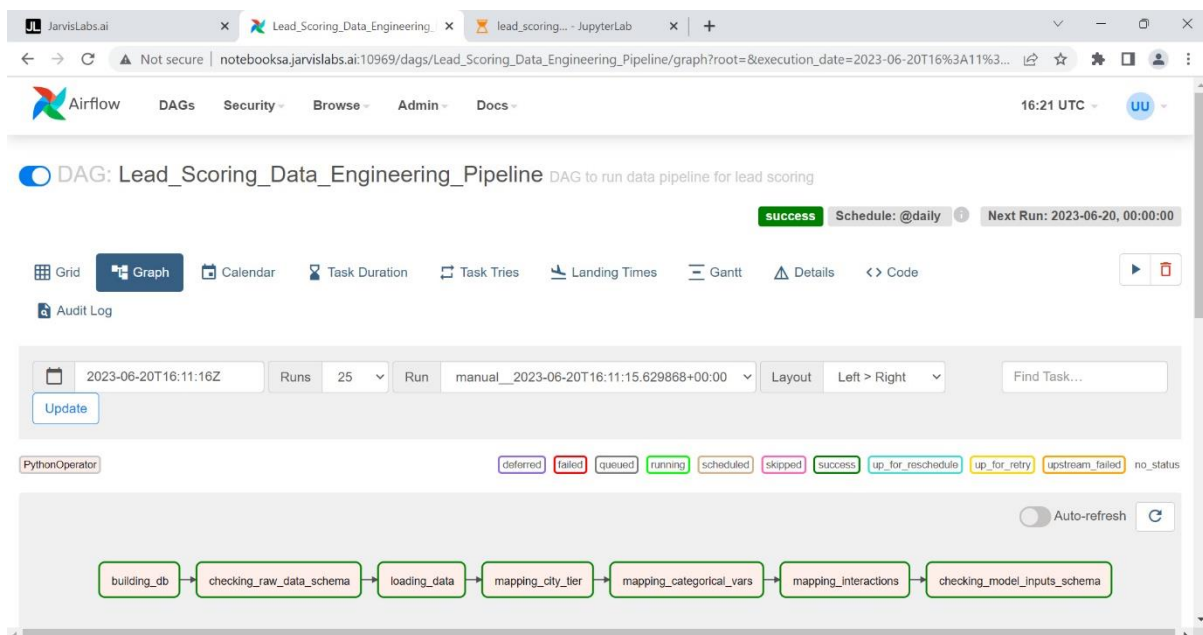


Figure 3: Graph view of Lead_Scoring_Data_Engineering_Pipeline

Initial run of Lead_scoring_training_pipeline

We have triggered manual run of Lead_scoring_training_pipeline for training cleaned data.

Both manual and scheduled runs can be seen in picture. Manual runs have white coloured arrow on top of green bars in Grid view.

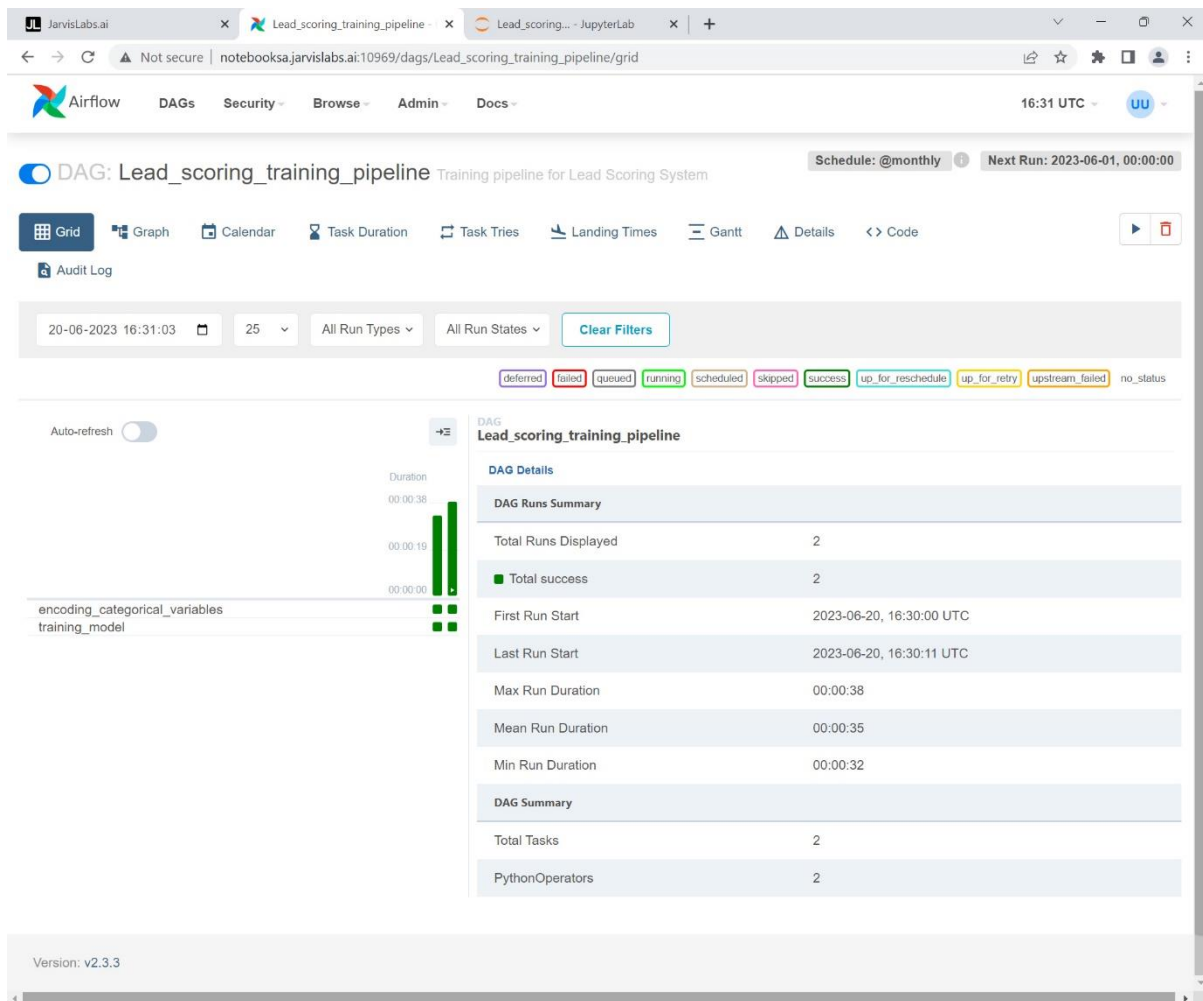


Figure 4: Grid view of Lead_scoring_training_pipeline

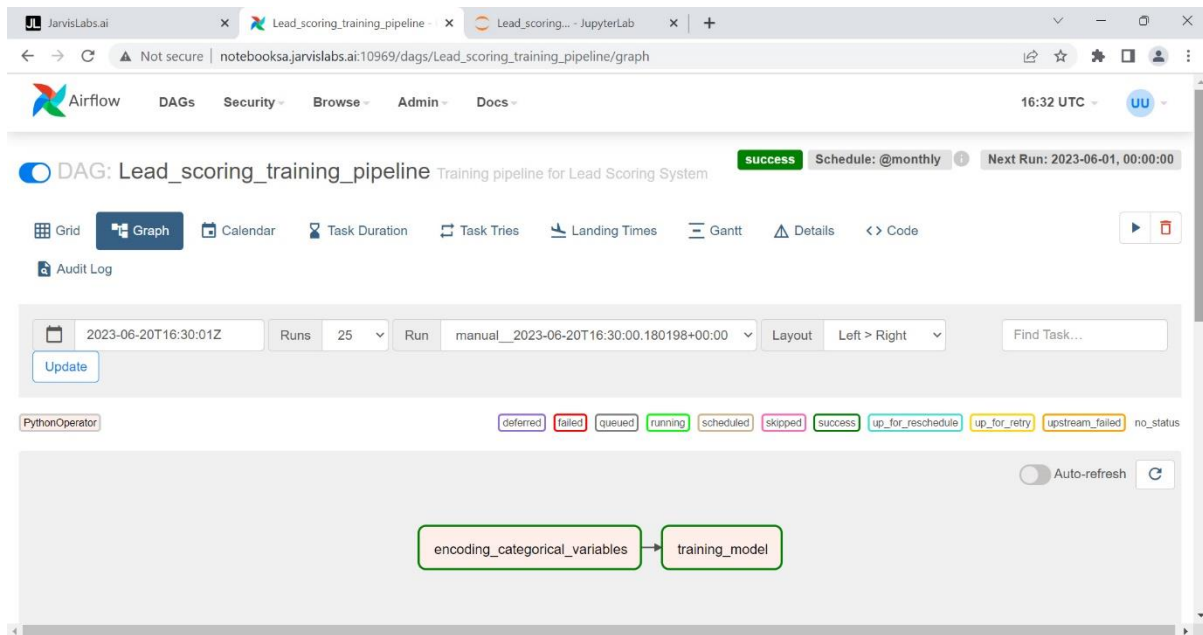


Figure 5: Graph view of Lead_scoring_training_pipeline

Initial run of Lead_scoring_inference_pipeline

We have triggered manual run of Lead_scoring_inference_pipeline for inferencing incoming data and predict outcome.

Both manual and scheduled runs can be seen in picture. Manual runs have white coloured arrow on top of green bars in Grid view.

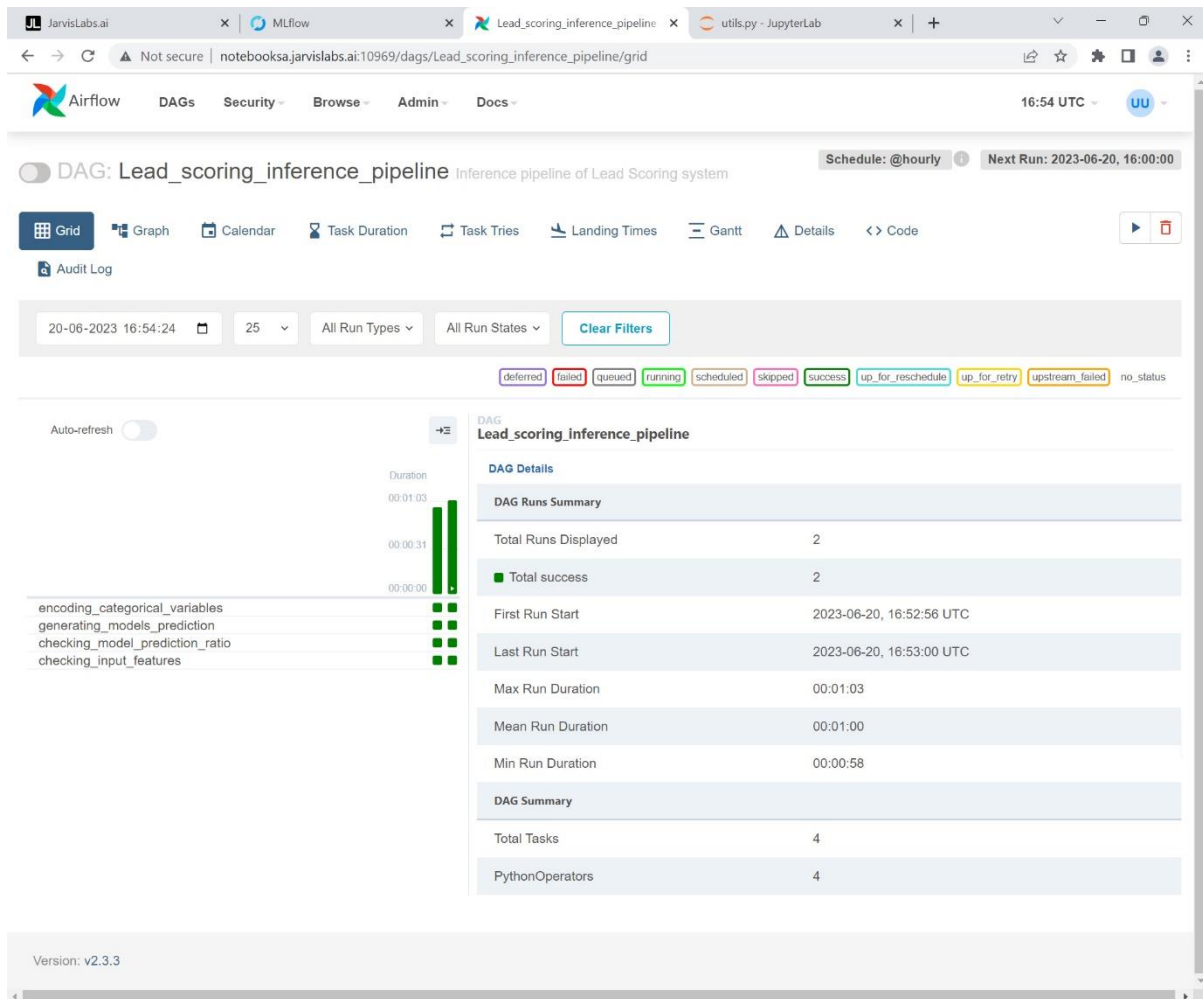


Figure 6: Grid view of Lead_scoring_inference_pipeline

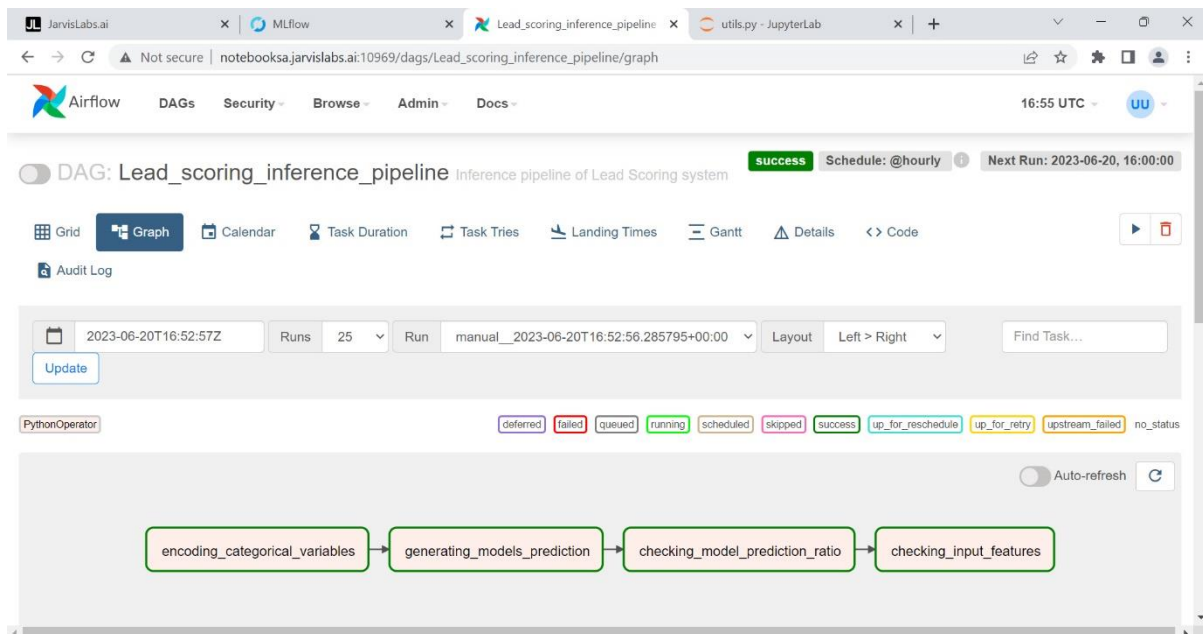


Figure 7: Graph view of Lead_scoring_inference_pipeline

Next run of Lead_Scoring_Data_Engineering_Pipeline

We have triggered manual run of Lead_Scoring_Data_Engineering_Pipeline for cleaning **leadscoring_inference.csv**.

Both manual and scheduled runs can be seen in picture. Manual runs have white coloured arrow on top of green bars in Grid view.

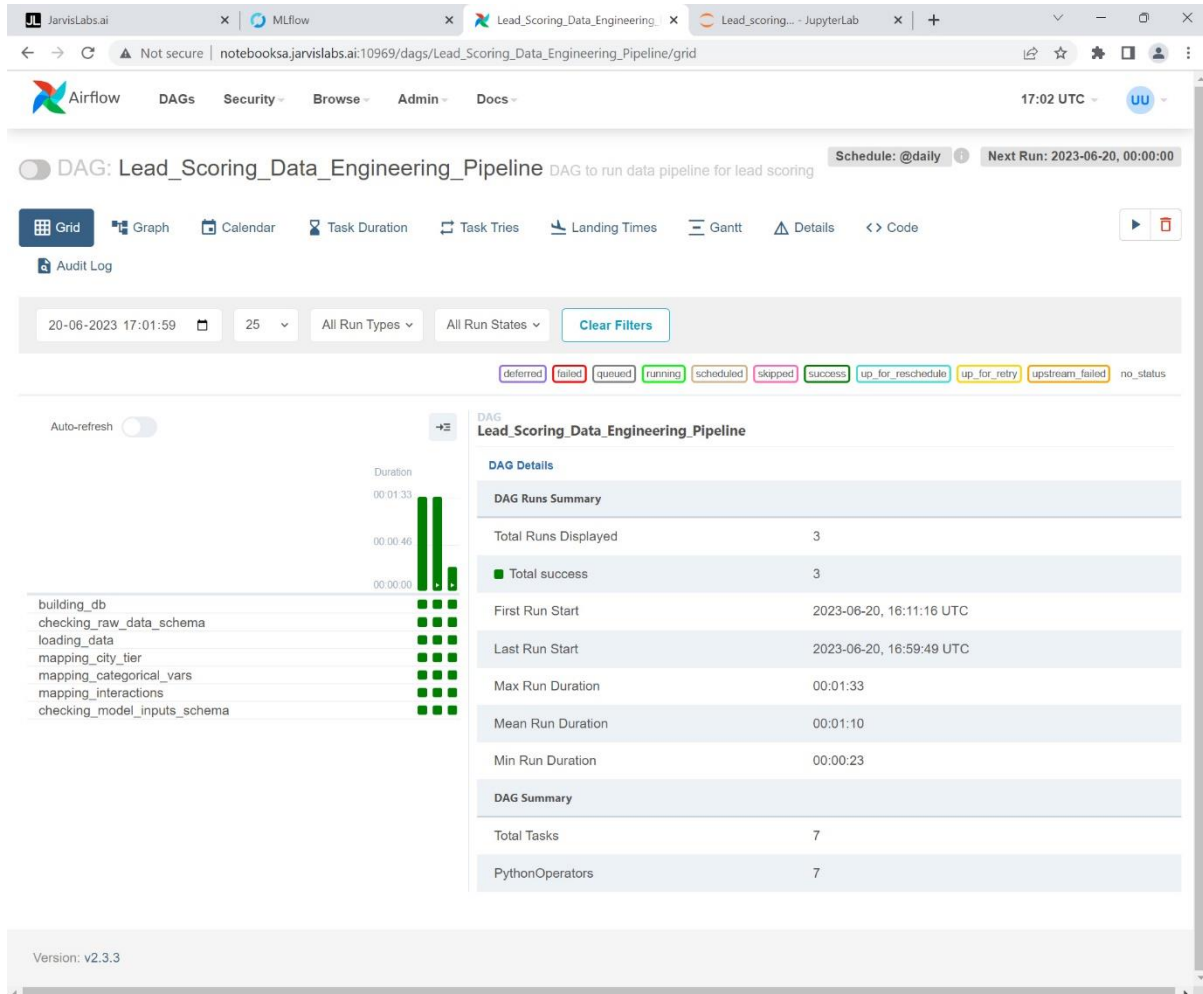


Figure 8: Grid view of Lead_Scoring_Data_Engineering_Pipeline

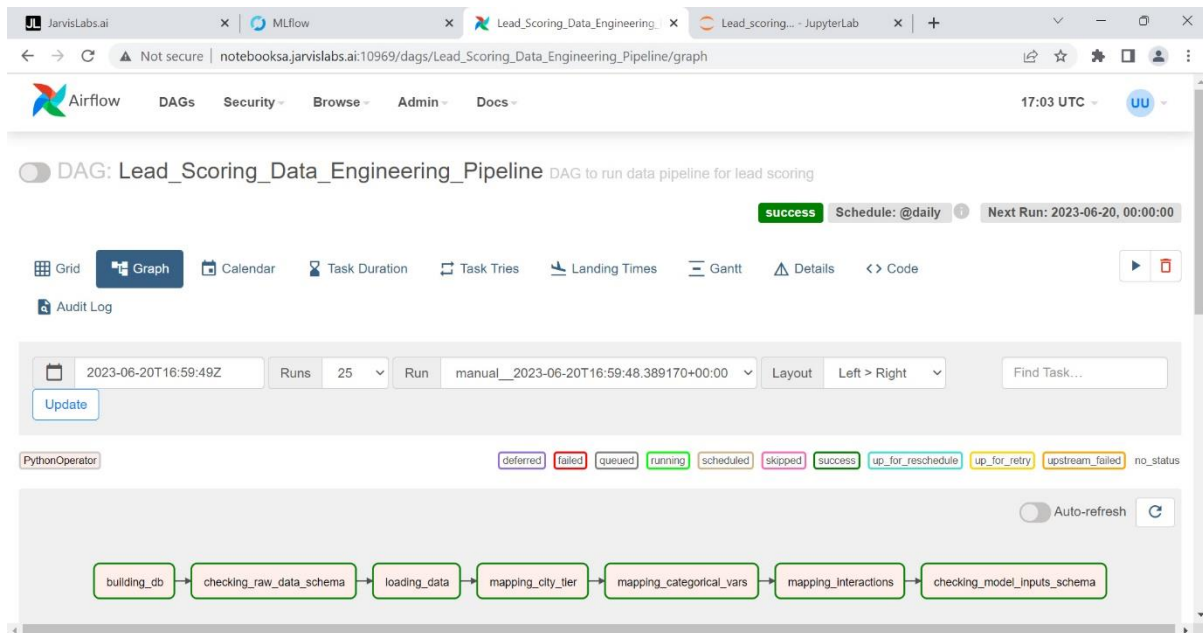


Figure 9: Graph view of Lead_Scoring_Data_Engineering_Pipeline

Next run of Lead_scoring_inference_pipeline

We have triggered manual run of Lead_scoring_inference_pipeline for inferencing incoming data and predict outcome.

Both manual and scheduled runs can be seen in picture. Manual runs have white coloured arrow on top of green bars in Grid view.

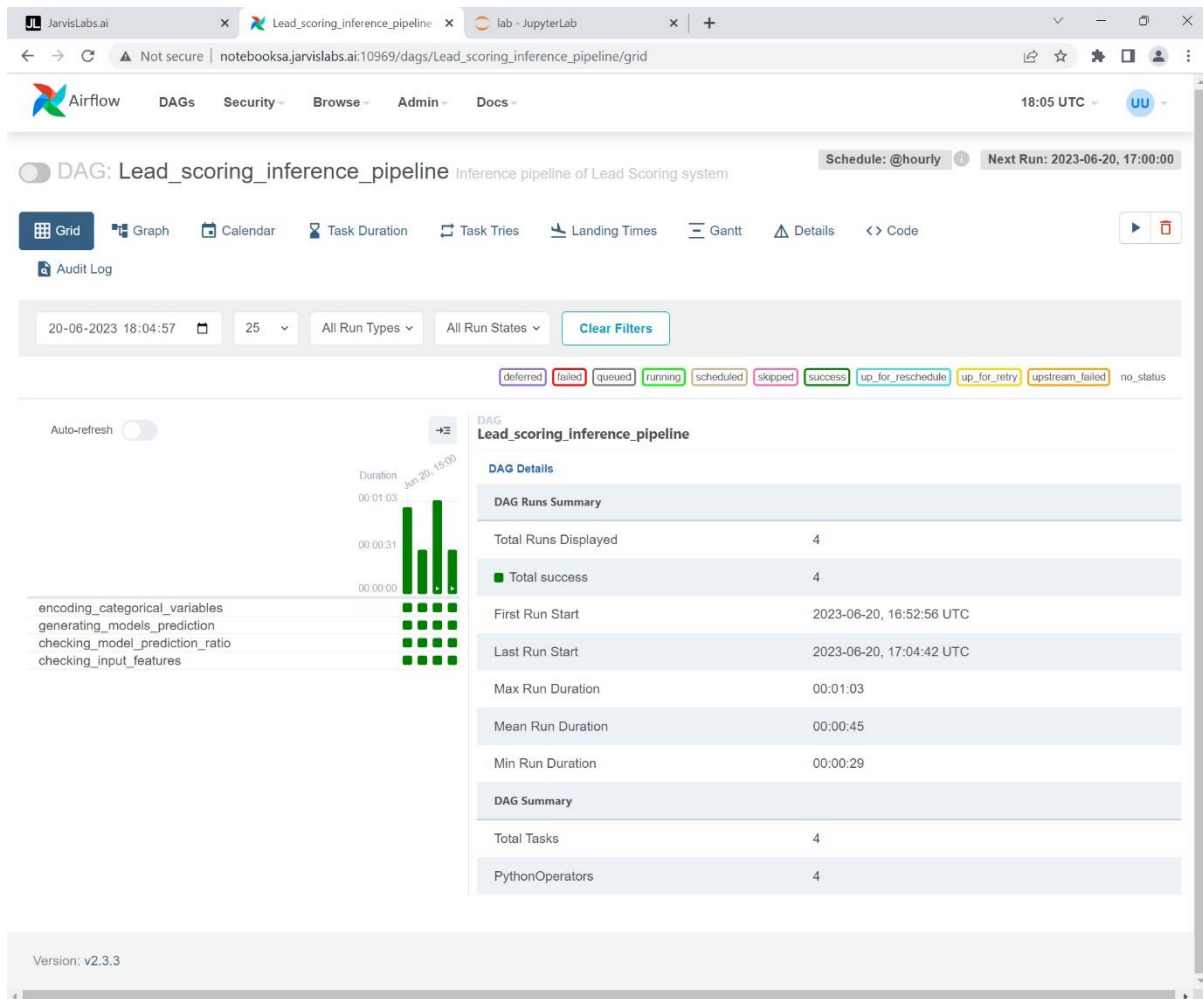


Figure 10: Grid view of Lead_scoring_inference_pipeline

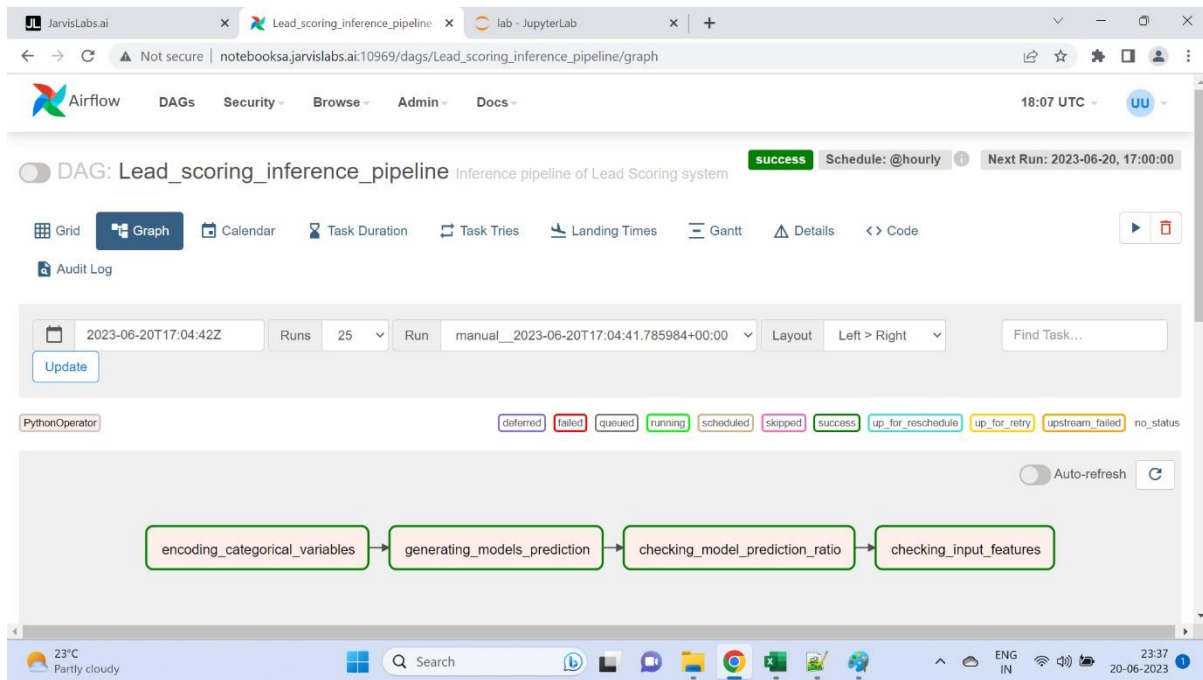


Figure 11: Graph view of Lead_scoring_inference_pipeline

MLFlow of Baseline_model_exp01

Baseline_model_exp01 is the initial pycaret setup experiment done for training model.

The image shows the MLFlow web interface for an experiment named 'Baseline_model_exp01'. The interface includes a top navigation bar with 'mlflow', 'Experiments', and 'Models'. The 'Experiments' tab is selected, showing a list of experiments on the left and details for 'Baseline_model_exp01' on the right. The details section includes a description, a table of runs, and a search bar. The table shows 11 matching runs, with the first run highlighted. The table has columns for 'Start Time', 'Duration', 'Run Name', 'User', 'Source', 'Version', 'Models', and 'Metrics'. The first run is '14 minutes ago' with a duration of 'Session Initi...' and a user of 'root'.

Start Time	Duration	Run Name	User	Source	Version	Models	Metrics
14 minutes ago	Session Initi...		root	ipykernel...	-	-	-

Figure 12: Main MLFlow UI of Baseline_model_exp01

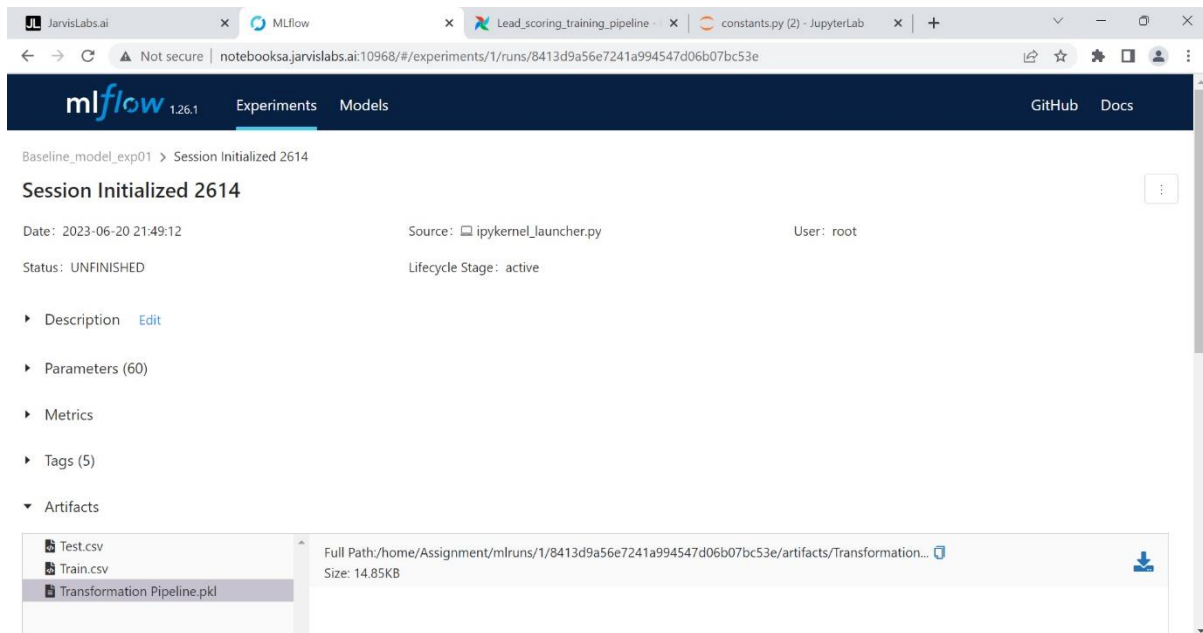


Figure 13: MLFlow Artifacts of Baseline_model_exp01

MLFlow of Baseline_model_exp02

Baseline_model_exp02 is the pycaret setup experiment done for training model **after removing certain features**.

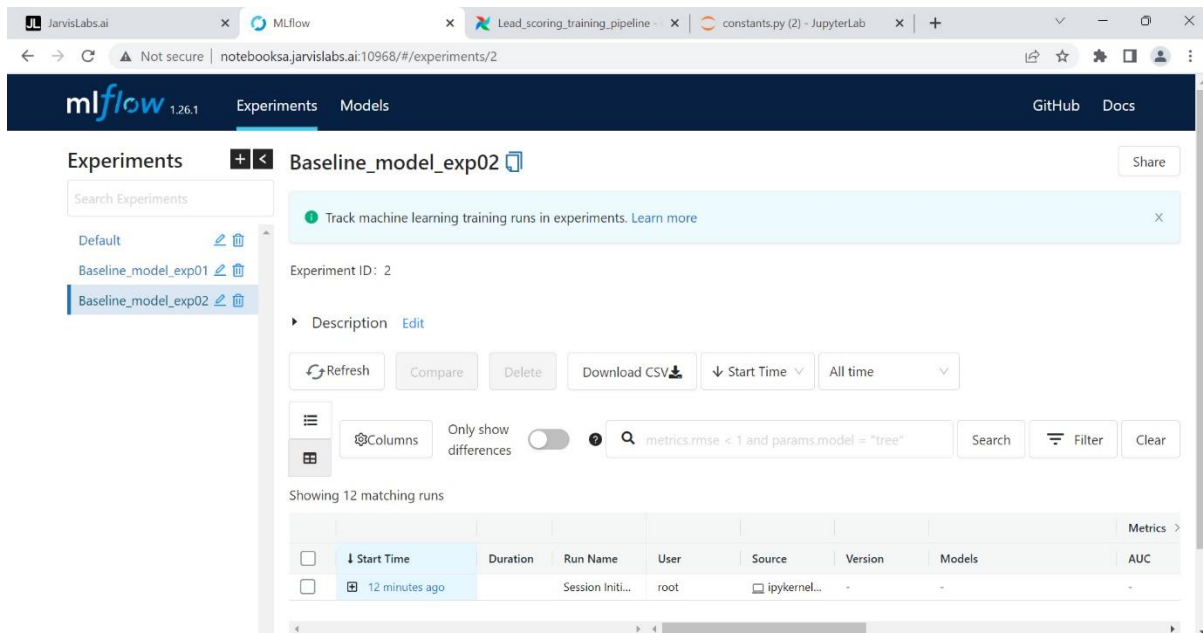


Figure 14: Main MLFlow UI of Baseline_model_exp02

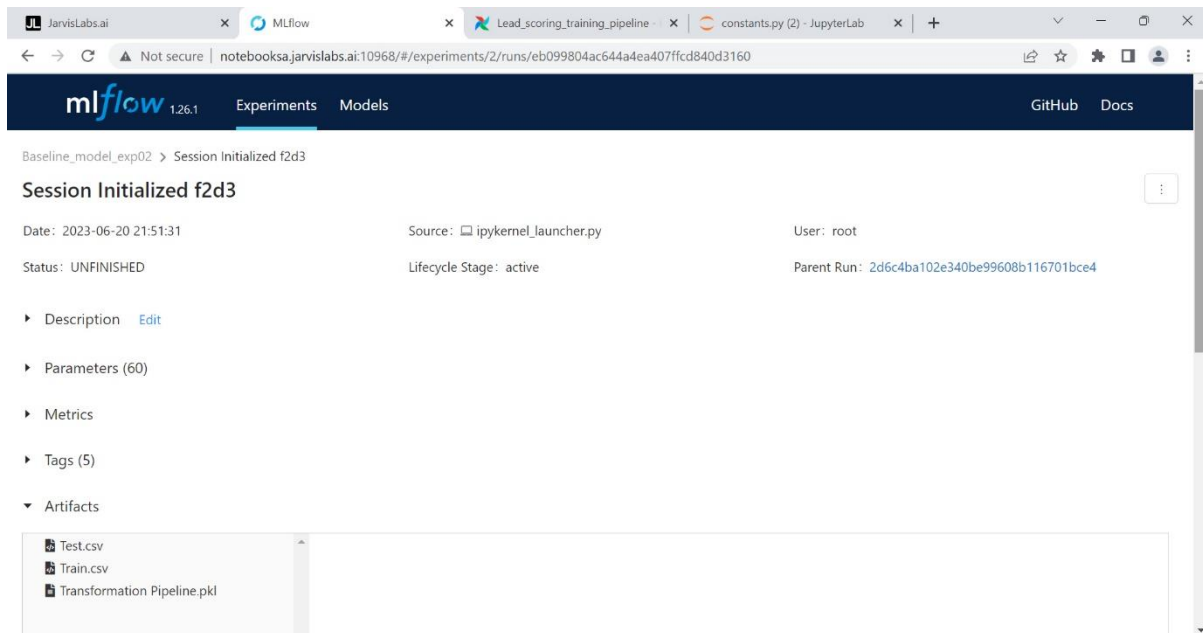


Figure 15: MLFlow Artifacts of Baseline_model_exp02

MLFlow of Lead_scoring_mlflow_production

Lead_scoring_mlflow_production is the final model we have selected. We can see 3 models are generated:

- **Version 1** - One was created when dummy notebook was run to check the working of utils.py functions.
- **Version 2** - One was created during schedule run of airflow (automatic).
- **Version 3** - One was created manually from airflow UI. This is our final model and we have moved this version to **PRODUCTION** stage.

Please check the figure captions to understand the following screenshots.

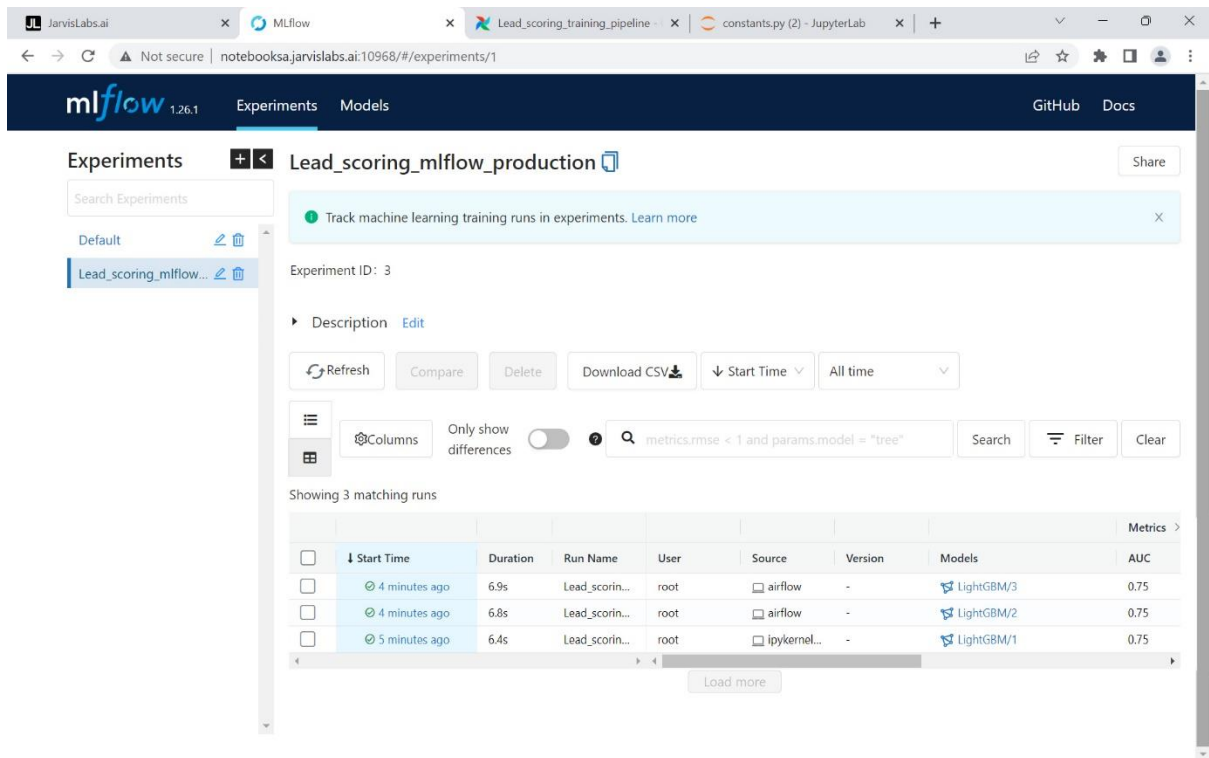


Figure 16: Main MLFlow UI of Lead_scoring_mlflow_production

Lead_scoring_mlflow_production > Lead_scoring_mlflow_production_20_06_2023

Lead_scoring_mlflow_production_20_06_2023

Date: 2023-06-20 21:59:22 Source: `ipykernel_launcher.py` User: root

Duration: 6.4s Status: FINISHED Lifecycle Stage: active

- Description [Edit](#)
- Parameters (20)
- Metrics (9)
- Tags
- Artifacts

models

- MLmodel
- conda.yaml
- model.pkl
- python_env.yaml
- requirements.txt

Full Path: `/home/Assignment/mlruns/3/8b4a64d02c9240019cbc8c116d1a5e6c/artifacts/models`

LightGBM, v1
Registered on 2023/06/20

MLflow Model

The code snippets below demonstrate how to make predictions using the logged model. This model is also registered to the [model registry](#).

Model schema

Input and output schema for your model. [Learn more](#)

Name	Type
No schema. See MLflow docs for how to include input and output schema with your model.	

Make Predictions

Predict on a Spark DataFrame:

```
import mlflow
logged_model = 'runs:/8b4a64d02c9240019cbc8c116d1a5e6c/models'

# Load model as a Spark UDF. Override result_type if the model does not return double values.
loaded_model = mlflow.pyfunc.spark_udf(spark, model_uri=logged_model, result_type='double')

# Predict on a Spark DataFrame.
columns = list(df.columns)
df.withColumn('predictions', loaded_model(*columns)).collect()
```

Predict on a Pandas DataFrame:

```
import mlflow
logged_model = 'runs:/8b4a64d02c9240019cbc8c116d1a5e6c/models'

# Load model as a PyFuncModel.
loaded_model = mlflow.pyfunc.load_model(logged_model)

# Predict on a Pandas DataFrame.
import pandas as pd
loaded_model.predict(pd.DataFrame(data))
```

Figure 17: MLFlow Artifacts of Version 1 model

Lead_scoring_mlflow_production > Lead_scoring_mlflow_production_20_06_2023

Lead_scoring_mlflow_production_20_06_2023

Date: 2023-06-20 22:00:25 Source: airflow User: root

Duration: 6.8s Status: FINISHED Lifecycle Stage: active

Description Edit

Parameters (20)

Metrics (9)

Tags

Artifacts

models

- MLmodel
- conda.yaml
- model.pkl
- python_env.yaml
- requirements.txt

Full Path: /home/Assignment/mlruns/3/5adfbe1e52fc41d4a5260c8fe740d88b/artifacts/models

LightGBM, v2
Registered on 2023/06/20

MLflow Model

The code snippets below demonstrate how to make predictions using the logged model. This model is also registered to the [model registry](#).

Model schema

Input and output schema for your model. [Learn more](#)

Name	Type
------	------

No schema. See [MLflow docs](#) for how to include input and output schema with your model.

Make Predictions

Predict on a Spark DataFrame:

```
import mlflow
logged_model = 'runs:/5adfbe1e52fc41d4a5260c8fe740d88b/models'

# Load model as a Spark UDF. Override result_type if the model does not return double values.
loaded_model = mlflow.pyfunc.spark_udf(spark, model_uri=logged_model, result_type='double')

# Predict on a Spark DataFrame.
columns = list(df.columns)
df.withColumn('predictions', loaded_model(*columns)).collect()
```

Predict on a Pandas DataFrame:

```
import mlflow
logged_model = 'runs:/5adfbe1e52fc41d4a5260c8fe740d88b/models'

# Load model as a PyFuncModel.
loaded_model = mlflow.pyfunc.load_model(logged_model)

# Predict on a Pandas DataFrame.
import pandas as pd
loaded_model.predict(pd.DataFrame(data))
```

Figure 18: MLFlow Artifacts of Version 2 model

MLflow 1.26.1ExperimentsModelsGitHubDocs

Lead_scoring_mlflow_production > Lead_scoring_mlflow_production_20_06_2023

Date: 2023-06-20 22:00:42

Source: airflow

User: root

Duration: 6.9s

Status: FINISHED

Lifecycle Stage: active

Description

Edit

Parameters (20)

Name	Value
boosting_type	gbdt
class_weight	None
colsample_bytree	1.0
importance_type	split
learning_rate	0.1
max_depth	-1
min_child_samples	20
min_child_weight	0.001
min_split_gain	0.0
n_estimators	100
n_jobs	-1
num_leaves	31
objective	None
random_state	42
reg_alpha	0.0
reg_lambda	0.0
silent	warn
subsample	1.0
subsample_for_bin	200000
subsample_freq	0

Metrics (9)

Name	Value
AUC	0.75
False Negative	3939
False Positive	8430
Precision	0.74
Recall	0.75
True Negative	15213
True Positive	20211
F1	0.738
test_accuracy	0.741

Tags

Artifacts

models

- MLmodel
- conda.yaml
- model.pkl
- python_env.yaml
- requirements.txt

Full Path: /home/Assignment/mlruns/3/52365e3cf06b40de9ee2d036677c86e1/artifacts/models

LightGBM, v1

Registered on 2023/06/20

MLflow Model

The code snippets below demonstrate how to make predictions using the logged model. This model is also registered to the model registry.

Model schema

Input and output schema for your model. [Learn more](#)

Name	Type
No schema. See MLflow docs for how to include input and output schema with your model.	

Make Predictions

Predict on a Spark DataFrame:

```
import mlflow
logged_model = 'runs:/52365e3cf06b40de9ee2d036677c86e1/models'

# Load model as a Spark UDF. Override result_type if the model does not return double values.
loaded_model = mlflow.pyfunc.spark_udf(spark, model_uri=logged_model, result_type='double')

# Predict on a Spark DataFrame.
columns = list(df.columns)
df.withColumn('predictions', loaded_model(*columns)).collect()
```

Predict on a Pandas DataFrame:

```
import mlflow
logged_model = 'runs:/52365e3cf06b40de9ee2d036677c86e1/models'

# Load model as a PyFuncModel.
loaded_model = mlflow.pyfunc.load_model(logged_model)

# Predict on a Pandas DataFrame.
import pandas as pd
loaded_model.predict(pd.DataFrame(data))
```

Figure 19: MLflow Artifacts of Version 3 model

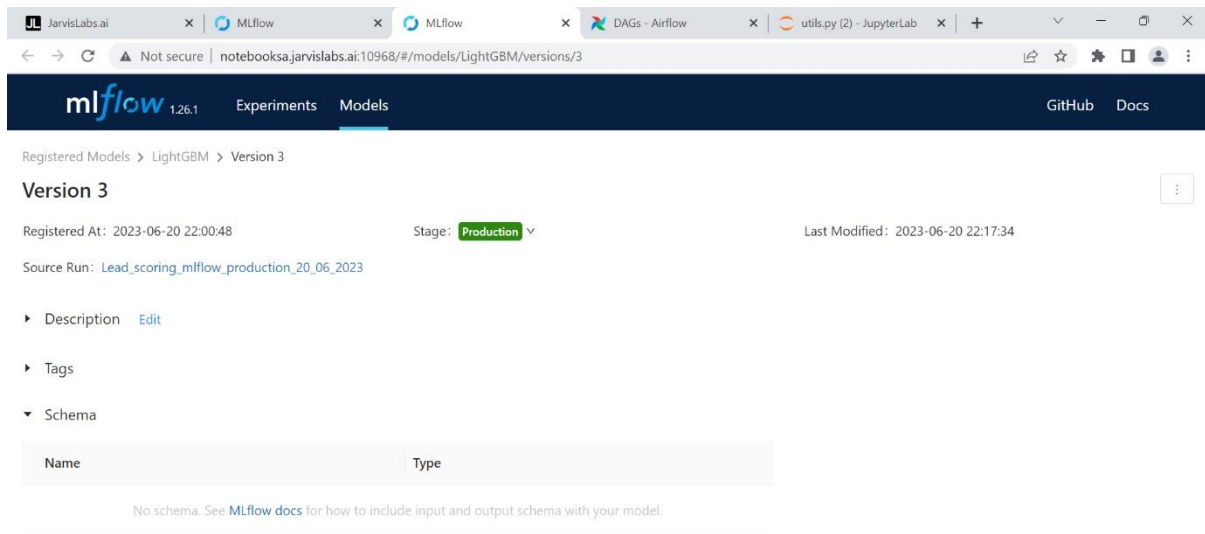


Figure 20: Version 3 model registered as Production Stage

Pytest of Data Pipeline

Screenshot of pytest done for data pipeline.

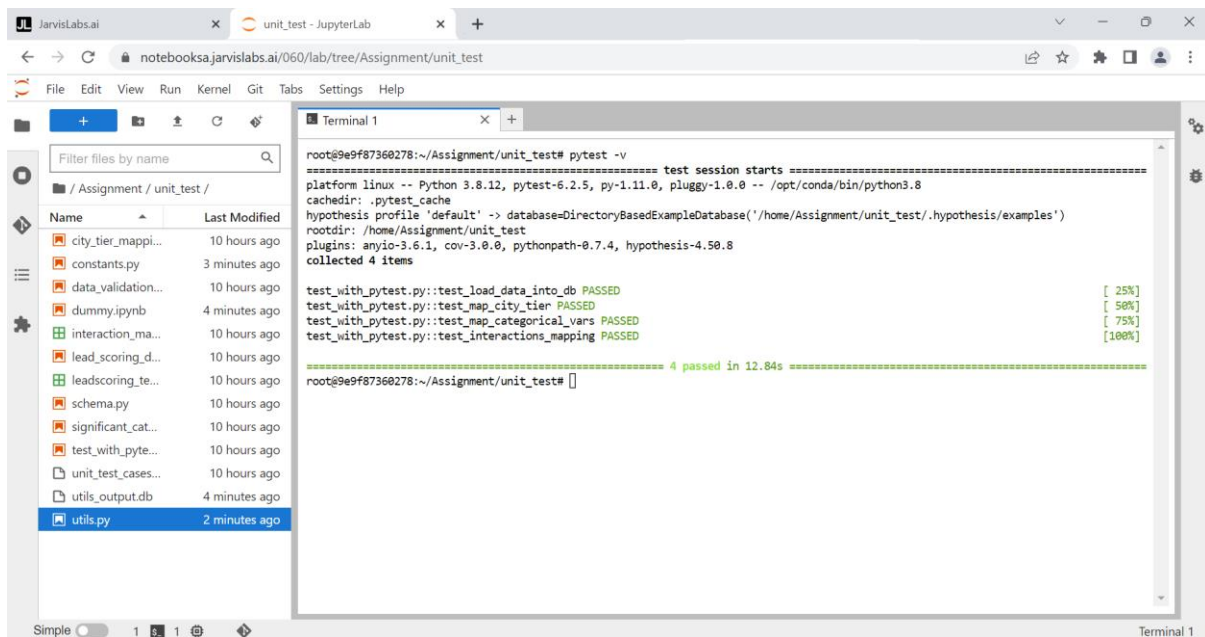


Figure 21: Pytest Test Results