## Q1. Install MLflow

To get started with MLflow you'll need to install the MLflow Python package.

For this we recommend creating a separate Python environment, for example, you can use <u>conda environments</u>, and then install the package there with pip or conda.

Once you installed the package, run the command mlflow --version and check the output.

What's the version that you have?

### **Answer**

### 2.14.1

```
PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS 3

(base) ubuntu@ip-172-31-38-150:-/mlops-training/module-2/notebooks/homework$ conda create -n mlops-zoomcamp-module2 python=3.11.7

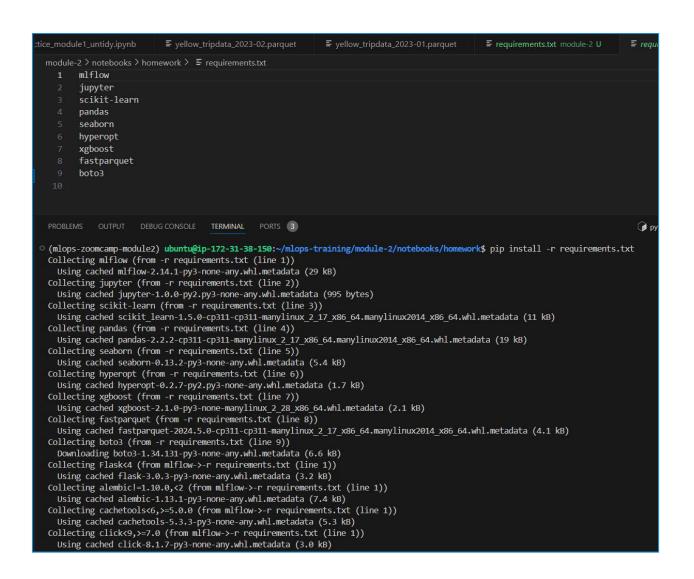
Retrieving notices: ...working... done
Channels:
- defaults
Platform: linux-64

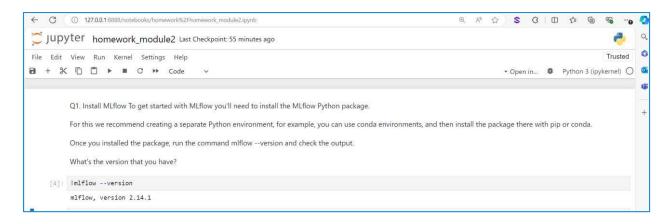
collecting package metadata (repodata.json): done
Solving environment: done

## Package Plan ##

environment location: /home/ubuntu/anaconda3/envs/mlops-zoomcamp-module2

added / updated specs:
- python=3.11.7
```





# Q2. Download and preprocess the data

We'll use the Green Taxi Trip Records dataset to predict the duration of each trip.

Download the data for January, February and March 2023 in parquet format from here.

Use the script preprocess\_data.py located in the folder homework to preprocess the data.

The script will:

- load the data from the folder <TAXI\_DATA\_FOLDER> (the folder where you have downloaded the data),
- fit a DictVectorizer on the training set (January 2023 data),
- save the preprocessed datasets and the DictVectorizer to disk.

Your task is to download the datasets and then execute this command:

```
python preprocess_data.py --raw_data_path <TAXI_DATA_FOLDER> --dest_path ./output
```

Tip: go to 02-experiment-tracking/homework/ folder before executing the command and change the value of <TAXI\_DATA\_FOLDER> to the location where you saved the data.

How many files were saved to OUTPUT FOLDER?

- 1
- 3
- 4
- 7

#### **Answer**

• 4

```
Jupyter homework_module2 Last Checkpoint: 1 hour ago
File Edit View Run Kernel Settings Help
                                                                                                                                                                                                                → Open in... • Python 3 (ipykernel) ○
a + % □ □ b ■ C >> Code
        [5]: |wget https://d37ci6vzurychx.cloudfront.net/trip-data/green_tripdata_2023-01.parquet -0 ../data/green_tripdata_2023-01.parquet
                | lwget https://d37ci6vzurychx.cloudfront.net/trip-data/green_tripdata_2023-02.parquet -0 ../data/green_tripdata_2023-02.parquet | lwget https://d37ci6vzurychx.cloudfront.net/trip-data/green_tripdata_2023-03.parquet -0 ../data/green_tripdata_2023-03.parquet
                 --2024-06-22 18:23:37-- https://d37ci6vzurychx.cloudfront.net/trip-data/green_tripdata_2023-01.parquet
Resolving d37ci6vzurychx.cloudfront.net (d37ci6vzurychx.cloudfront.net)... 13.32.192.190, 13.32.192.2, 13.32.192.116, ...
Connecting to d37ci6vzurychx.cloudfront.net (d37ci6vzurychx.cloudfront.net)|13.32.192.190|:443... connected.
                 HTTP request sent, awaiting response... 200 OK
Length: 1427002 (1.4M) [binary/octet-stream]
Saving to: '../data/green_tripdata_2023-01.parquet'
                 ../data/green_tripd 100%[=========>] 1.36M --.-KB/s in 0.03s
                 2024-06-22 18:23:38 (41.7 MB/s) - '../data/green_tripdata_2023-01.parquet' saved [1427002/1427002]
                 --2024-06-22 18:23:38-- https://d37ci6vzurychx.cloudfront.net/trip-data/green_tripdata_2023-02.parquet
Resolving d37ci6vzurychx.cloudfront.net (d37ci6vzurychx.cloudfront.net)... 13.32.192.2, 13.32.192.116, 13.32.192.124, ...
                 nesotring us/taveau/sinx.touurront.net (us/taveau/sinx.touurront.net)... 15.32.192.2; 15.32.192.116, 15.
Connecting to d37ci6vzurychx.cloudfront.net (d37ci6vzurychx.cloudfront.net)|13.32.192.2|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 1533740 (1.5M) [binary/octet-stream]
                 Saving to: '../data/green_tripdata_2023-02.parquet'
                 ../data/green_tripd 100%[==========] 1.46M --.-KB/s in 0.02s
                 2024-06-22 18:23:38 (78.1 MB/s) - '../data/green_tripdata_2023-02.parquet' saved [1533740/1533740]
                 --2024-06-22 18:23:39-- https://d37ci6vzurychx.cloudfront.net/trip-data/green_tripdata_2023-03.parquet
Resolving d37ci6vzurychx.cloudfront.net (d37ci6vzurychx.cloudfront.net)... 13.32.192.2, 13.32.192.116, 13.32.192.124, ...
Connecting to d37ci6vzurychx.cloudfront.net (d37ci6vzurychx.cloudfront.net)|13.32.192.2|:443... connected.
                 HTTP request sent, awaiting response... 200 OK
Length: 1730999 (1.7M) [binary/octet-stream]
Saving to: '../data/green_tripdata_2023-03.parquet'
                 ../data/green_tripd 100%[========>] 1.65M --.-KB/s in 0.02s
                 2024-06-22 18:23:39 (86.4 MB/s) - '.../data/green_tripdata_2023-03.parquet' saved [1730999/1730999]
```

#### Running preprocess file and printing the count of files in output folder

## Q3. Train a model with autolog

We will train a RandomForestRegressor (from Scikit-Learn) on the taxi dataset.

We have prepared the training script train.py for this exercise, which can be also found in the folder <a href="https://example.com/homework">homework</a>.

The script will:

- load the datasets produced by the previous step,
- train the model on the training set,
- calculate the RMSE score on the validation set.

Your task is to modify the script to enable **autologging** with MLflow, execute the script and then launch the MLflow UI to check that the experiment run was properly tracked.

Tip 1: don't forget to wrap the training code with a with mlflow.start\_run(): statement as we showed in the videos.

Tip 2: don't modify the hyperparameters of the model to make sure that the training will finish quickly.

What is the value of the min\_samples\_split parameter:

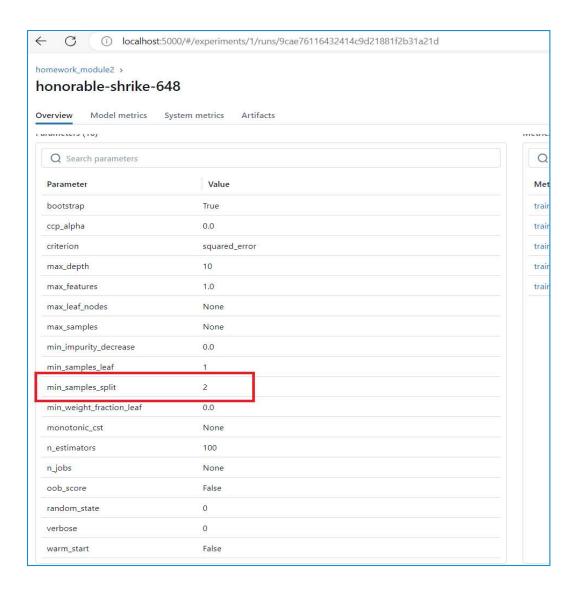
- 2
- 4
- 8
- 10

#### Answer

• 2

```
C
       (i) localhost:8888/edit/notebooks/homework/train.py
             Jupyter train.py Last Checkpoint: 22 hours ago
             File Edit View Settings Help
             缸
             1 import os
             2 import pickle
             3 import click
             4 import mlflow
             6 from sklearn.ensemble import RandomForestRegressor
             7 from sklearn.metrics import mean_squared_error
             8
9 # Adding tracking uri and creating experiment if does not exist
            10 mlflow.set_tracking_uri("sqlite:///mlflow.db")
               mlflow.set_experiment("homework_module2")
            13 def load_pickle(filename: str):
                  with open(filename, "rb") as f_in:
            14
            15
                       return pickle.load(f_in)
```

```
21
       default="./output",
       help="Location where the processed NYC taxi trip data was saved"
22
23 )
24 def run_train(data_path: str):
25
26
       # Adding autolog
27
       mlflow.sklearn.autolog()
28
       X train, y train = load pickle(os.path.join(data path, "train.pkl"))
29
       X_val, y_val = load_pickle(os.path.join(data_path, "val.pkl"))
30
       # wrapping the training code with a with mlflow.start run()
31
32
       with mlflow.start_run():
33
           rf = RandomForestRegressor(max depth=10, random state=0)
34
           rf.fit(X_train, y_train)
35
           y_pred = rf.predict(X_val)
36
37
           rmse = mean_squared_error(y_val, y_pred, squared=False)
38
39
40 if name == ' main ':
41
       run train()
```



## Q4. Launch the tracking server locally

Now we want to manage the entire lifecycle of our ML model. In this step, you'll need to launch a tracking server. This way we will also have access to the model registry.

Your task is to:

- launch the tracking server on your local machine,
- select a SQLite db for the backend store and a folder called artifacts for the artifacts store.

You should keep the tracking server running to work on the next two exercises that use the server.

In addition to backend-store-uri, what else do you need to pass to properly configure the server?

- default-artifact-root
- serve-artifacts
- artifacts-only
- artifacts-destination

#### **Answer**

### default-artifact-root

## Q5. Tune model hyperparameters

Now let's try to reduce the validation error by tuning the hyperparameters of the RandomForestRegressor using hyperopt. We have prepared the script hpo.py for this exercise.

Your task is to modify the script hpo.py and make sure that the validation RMSE is logged to the tracking server for each run of the hyperparameter optimization (you will need to add a few lines of code to the objective function) and run the script without passing any parameters.

After that, open UI and explore the runs from the experiment called random-foresthyperopt to answer the question below.

Note: Don't use autologging for this exercise.

The idea is to just log the information that you need to answer the question below, including:

- the list of hyperparameters that are passed to the objective function during the optimization,
- the RMSE obtained on the validation set (February 2023 data).

What's the best validation RMSE that you got?

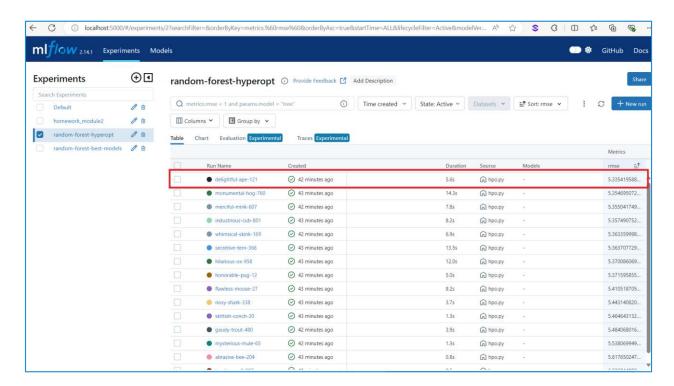
- 4.817
- 5.335
- 5.818
- 6.336

#### **Answer**

• 5.335

```
C
      (i) localhost:8888/edit/notebooks/homework/hpo.py
     Jupyter hpo.py Last Checkpoint: 20 minutes ago
                      Settings
         Edit
               View
                              Help
    ≢
    36
    37
           def objective(params):
    38
    39
               # wrapping the training code with a with mlflow.start_run()
               with mlflow.start_run():
   40
   41
   42
                   #logging params
   43
                   mlflow.log_params(params)
                   rf = RandomForestRegressor(**params)
   44
   45
                   rf.fit(X_train, y_train)
   46
                   y_pred = rf.predict(X_val)
   47
                   rmse = mean_squared_error(y_val, y_pred, squared=False)
                   #logging metric rmse
   48
                   mlflow.log_metric("rmse", rmse)
   49
   50
               return {'loss': rmse, 'status': STATUS_OK}
   51
   52
           search_space = {
   53
               'max_depth': scope.int(hp.quniform('max_depth', 1, 20, 1)),
   54
               'n_estimators': scope.int(hp.quniform('n_estimators', 10, 50, 1)),
   55
               'min_samples_split': scope.int(hp.quniform('min_samples_split', 2, 10, 1)),
   56
   57
               'min_samples_leaf': scope.int(hp.quniform('min_samples_leaf', 1, 4, 1)),
               'random_state': 42
   58
   59
   60
           rstate = np.random.default_rng(42) # for reproducible results
   61
   62
           fmin(
   63
               fn=objective,
   64
               space=search_space,
   65
               algo=tpe.suggest,
   66
               max evals=num trials,
   67
               trials=Trials(),
   68
               rstate=rstate
           )
   69
```





## Q6. Promote the best model to the model registry

The results from the hyperparameter optimization are quite good. So, we can assume that we are ready to test some of these models in production. In this exercise, you'll promote the best model to the model registry. We have prepared a script called register\_model.py, which will check the results from the previous step and select the top 5 runs. After that, it will calculate the RMSE of those models on the test set (March 2023 data) and save the results to a new experiment called random-forest-best-models.

Your task is to update the script register\_model.py so that it selects the model with the lowest RMSE on the test set and registers it to the model registry.

Tip 1: you can use the method search\_runs from the MlflowClient to get the model with the lowest RMSE,

Tip 2: to register the model you can use the method mlflow.register\_model and you will need to pass the right model\_uri in the form of a string that looks like this: "runs:/<RUN ID>/model", and the name of the model (make sure to choose a good one!).

What is the test RMSE of the best model?

- 5.060
- 5.567
- 6.061
- 6.568

### **Answer**

• 5.567

