Team13_Uber&Lyft_Price_prediction

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1 Team13 Uber and Lyft Surge Price Prediction

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1.1 Background

As residents living in the Boston area, we benefit from a convenient public transportation system, including commuter rail, subway lines, and bus routes. However, despite these options, sometimes schedules or routes may not fit our specific needs, prompting us to rely on services like Uber and Lyft for convenience. These ride-sharing apps have become an integral part of transportation in the Boston area, and pricing is an important factor in the decision-making process. When considering whether to choose Uber or Lyft, the first thing that comes to mind is price, as people often open both apps to compare and choose the more economical option.

Several factors contribute to price fluctuations on these platforms. For example, demand and supply dynamics play a crucial role, with peak periods or high demand causing higher price. In addition, external factors such as weather conditions, traffic or distance can also affect the cost of a ride. The availability of different vehicle types and service levels also results in different price points.

1.2 Problem Statement

In this project, our primary objective is to provide a prediction of Uber and Lyft surge prices under different weather and geolocation factors, such as: temperature, rain, wind, pick up location, and destination, to enhance passengers' ability to make informed booking decisions.

We aim to solve the problem of fluctuating Uber and Lyft fares under the influence of unpredictable surge pricing, offering passengers a reliable tool to estimate the cost of their trips.

Our analysis is geared towards examining the Uber and Lyft trips in Boston during 11/26/2018 to.12/18/2018. By finding the most related factors that affect fare prices, we will first use Linear Regression, Decision Tree Regression, Elastic Net Regression, and XGBoost Regression models to find the most accurate model for prediction. Then, we will use feature importance to pinpoint the most important factors that influence price for Uber and Lyft separately.

1.3 Problem importance

Provide budgeting suggestions for passengers:

Our predictive model is designed to predict Uber and Lyft fare prices by understanding the factors that influence surge pricing, including interactions between factors. Our predictive model allows travelers to enter specific trip details such as pick up location, destination, and vehicle type. This feature provides price estimates to travelers, allowing them to plan their budget and travel effectively.

Provide trip planning suggestions for passengers:

For passengers who are more flexible on their departure time, our model can also provide alternative times with more affordable prices. Furthermore, for passengers who are unsure about their pick up location, they can use our model to discover suitable locations based on their budget.

1.4 Dataset Description

Accessing Kaggle's data, cab_rides, and weather datasets provides a valuable opportunity to delve into the dynamics of Uber and Lyft taxi prices during the week of November-December 2018. The cab_rides data set consists of 10 columns and 693,070 rows and provides a comprehensive view of the various types of taxis offered by Uber and Lyft, including pricing and location information.

The weather dataset has 8 columns and 6,275 rows and provides information about weather attributes for various locations and books. This includes temperature, precipitation (rain) and cloud cover information. Integrating weather data into the analysis can provide a better understanding of how external factors such as weather conditions affect Uber and Lyft prices.

Datasource : Uber & Lyft Cab prices on Kaggle: direct access link here

Number of rows: 693,071 rows

Number of columns:

- cab_rides: 10 columns
- weather: 8 columns

Variable types: string, number, date, integer, boolean

Data description for cab_rides

Column title	Description
distance	distance between source and destination
cab_type	Uber or Lyft
time_stamp	epoch time when data was queried
destination	destination of the ride
source	the starting point of the ride
price	price estimate for the ride in USD
surge_multiplier	the multiplier by which price was increased, default 1
id	unique identifier

Column title	Description
product_id	uber/lyft identifier for cab-type
name	Visible type of the cab eg: Uber Pool, UberXL

Data description for weather

Column title	Description
temp	Temperature in F
location	Location name
clouds	Clouds
pressure	pressure in mb
rain	rain in inches for the last hr
time_stamp	epoch time when row data was collected
humidity	thumidity in %
wind	wind speed in mph

2 Data Processing

2.1 Import library & Document

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from google.colab import drive

%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
```

[ ]:
```
drive.mount('/content/drive')
cab_df = pd.read_csv("/content/drive/MyDrive/BA_810_Group13/cab_rides.csv")
weather = pd.read_csv("/content/drive/MyDrive/BA_810_Group13/weather.csv")
```

```
Mounted at /content/drive
```

2.2 Data Cleaning

2.2.1 Aligning cab_rides and weather units

Since the cab_df and weather use different time frequencies, we added a new column "merge_date" to take the average weather data by hour, and matched it to the trips table on the hour extracted from the timestamp.

[ ]:
```
# Unifing timestamp format and turn to datetime
cab_df['date_time'] = pd.to_datetime(cab_df['time_stamp']/1000, unit='s')
weather['date_time'] = pd.to_datetime(weather['time_stamp'], unit='s')
```

[ ]:
```python
# Create a new column for merging, and imputing rain columns with 0
cab_df['merge_date'] = cab_df['source'].astype(str) + " - " +
↪cab_df['date_time'].dt.date.astype(str) + " - " + cab_df['date_time'].dt.
↪hour.astype(str)
weather['merge_date'] = weather['location'].astype(str) + " - " +
↪weather['date_time'].dt.date.astype(str) + " - " + weather['date_time'].dt.
↪hour.astype(str)

groupby_value = weather.groupby(['merge_date']).mean().reset_index()
groupby_value['rain'].fillna(0,inplace=True)
```

[ ]:
```python
# Merge two dataframe and drop NAN
groupby_value.index = groupby_value['merge_date']
merged_df = cab_df.join(groupby_value,on=['merge_date'],rsuffix ='_w')
merged_df.dropna(inplace=True)
merged_df.head(5)
```

[ ]:
```
   distance cab_type      time_stamp    destination            source  price  \
0      0.44     Lyft  1544952607890  North Station  Haymarket Square    5.0
1      0.44     Lyft  1543284023677  North Station  Haymarket Square   11.0
3      0.44     Lyft  1543553582749  North Station  Haymarket Square   26.0
4      0.44     Lyft  1543463360223  North Station  Haymarket Square    9.0
5      0.44     Lyft  1545071112138  North Station  Haymarket Square   16.5

   surge_multiplier                                    id    product_id  \
0               1.0  424553bb-7174-41ea-aeb4-fe06d4f4b9d7     lyft_line
1               1.0  4bd23055-6827-41c6-b23b-3c491f24e74d  lyft_premier
3               1.0  c2d88af2-d278-4bfd-a8d0-29ca77cc5512   lyft_luxsuv
4               1.0  e0126e1f-8ca9-4f2e-82b3-50505a09db9a     lyft_plus
5               1.0  f6f6d7e4-3e18-4922-a5f5-181cdd3fa6f2      lyft_lux

           name                     date_time  \
0        Shared 2018-12-16 09:30:07.890000128
1           Lux 2018-11-27 02:00:23.676999936
3  Lux Black XL 2018-11-30 04:53:02.749000192
4       Lyft XL 2018-11-29 03:49:20.223000064
5     Lux Black 2018-12-17 18:25:12.138000128

                        merge_date                       merge_date_w  \
0   Haymarket Square - 2018-12-16 - 9   Haymarket Square - 2018-12-16 - 9
1   Haymarket Square - 2018-11-27 - 2   Haymarket Square - 2018-11-27 - 2
3   Haymarket Square - 2018-11-30 - 4   Haymarket Square - 2018-11-30 - 4
4   Haymarket Square - 2018-11-29 - 3   Haymarket Square - 2018-11-29 - 3
5  Haymarket Square - 2018-12-17 - 18  Haymarket Square - 2018-12-17 - 18

     temp    clouds  pressure   rain  time_stamp_w  humidity   wind
0  38.460  0.290000   1022.25  0.000  1.544954e+09  0.760000   7.68
```

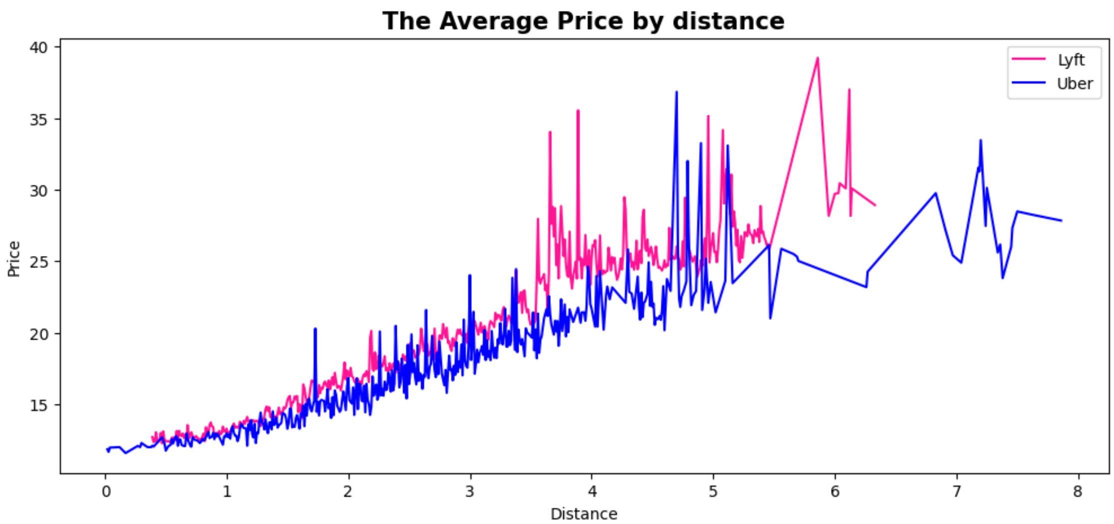
1	44.065	0.995000	1002.88	0.106	1.543286e+09	0.895000	12.63
3	35.080	0.000000	1013.71	0.000	1.543554e+09	0.700000	5.25
4	37.680	0.433333	998.42	0.000	1.543461e+09	0.706667	11.16
5	40.780	0.930000	1000.15	0.000	1.545072e+09	0.790000	7.55

3 Descriptive Analysis

3.1 Which apps have lower prices, Uber or Lyft?

Customers usually want to save money, so they usually open both apps to compare prices before making a decision. One of the main factors that affects prices is the distance between origin and destination. Using this data, we can look at the average price for each app based on distance traveled.

[ ]:
```
# plotting distance against price
fig , ax = plt.subplots(figsize = (12,5))
ax.plot(merged_df[merged_df['cab_type'] == 'Lyft'].groupby('distance').price.
 ↪mean().index,
        merged_df[merged_df['cab_type'] == 'Lyft'].groupby('distance').price.
 ↪mean(),
        label = 'Lyft', color='deeppink')

ax.plot(merged_df[merged_df['cab_type'] == 'Uber'].groupby('distance').price.
 ↪mean().index,
        merged_df[merged_df['cab_type'] =='Uber'].groupby('distance').price.
 ↪mean(),
        label = 'Uber', color='blue')

ax.set_title('The Average Price by distance', fontsize= 15, fontweight='bold')
ax.set(xlabel = 'Distance', ylabel = 'Price' )
ax.legend()
plt.show()
```



From above figure, we can observe that for long-distance trips (distances exceeding 5 miles), Lyft tends to have a higher price. Therefore, it is advisable to opt for Uber in such cases.

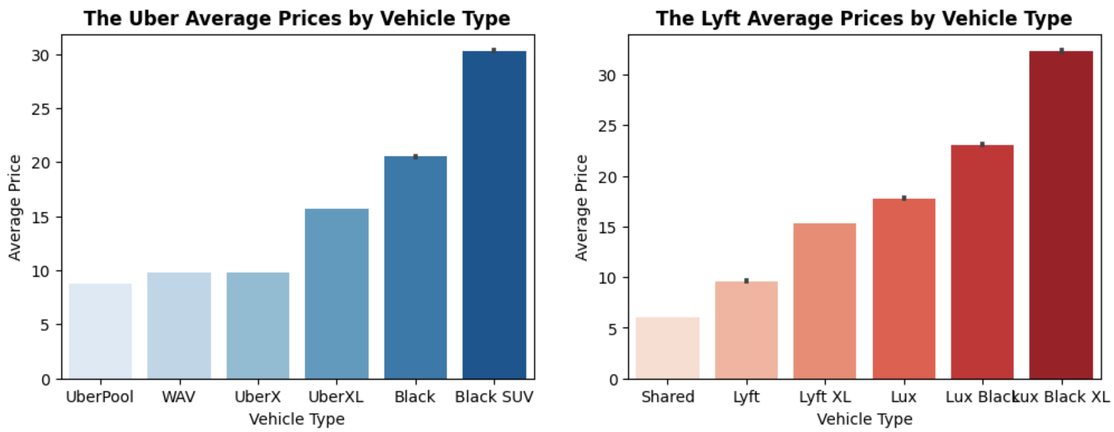
However, for short-distance trips (distances less than 5 miles), Uber can occasionally have higher costs.

3.2 Do Uber and Lyft have different prices for various vehicle types?

Sometimes customers are traveling with friends or family and require a larger vehicle, and other times they seek luxury travel. Therefore, it becomes crucial to understand which apps customers should choose based on vehicle type.

[ ]:
```
# plotting Vehicle Type against average price
uber_order =[ 'UberPool','WAV', 'UberX', 'UberXL', 'Black','Black SUV' ]
lyft_order = ['Shared', 'Lyft', 'Lyft XL', 'Lux', 'Lux Black', 'Lux Black XL']
fig, ax = plt.subplots(1,2, figsize = (12,4))
ax1 = sns.barplot(x = merged_df[merged_df['cab_type'] == 'Uber'].name,
                  y = merged_df[merged_df['cab_type'] == 'Uber'].price ,
                  ax = ax[0], order = uber_order,palette='Blues')

ax2 = sns.barplot(x = merged_df[merged_df['cab_type'] == 'Lyft'].name,
                  y = merged_df[merged_df['cab_type'] == 'Lyft'].price ,
                  ax = ax[1], order = lyft_order,palette='Reds')

ax1.set(xlabel = 'Vehicle Type', ylabel = 'Average Price')
ax2.set(xlabel = 'Vehicle Type', ylabel = 'Average Price')

ax1.set_title('The Uber Average Prices by Vehicle Type', fontweight='bold')
ax2.set_title('The Lyft Average Prices by Vehicle Type', fontweight='bold')
```

```
plt.show()
```



From above figures, comparing the price differences for various vehicle types, even when opting for shared rides, Uber (UberPool) tends to be more expensive than Lyft (Shared).

If you're looking for a smaller vehicle type, Lyft (Lyft) is generally more affordable compared to Uber (UberX).

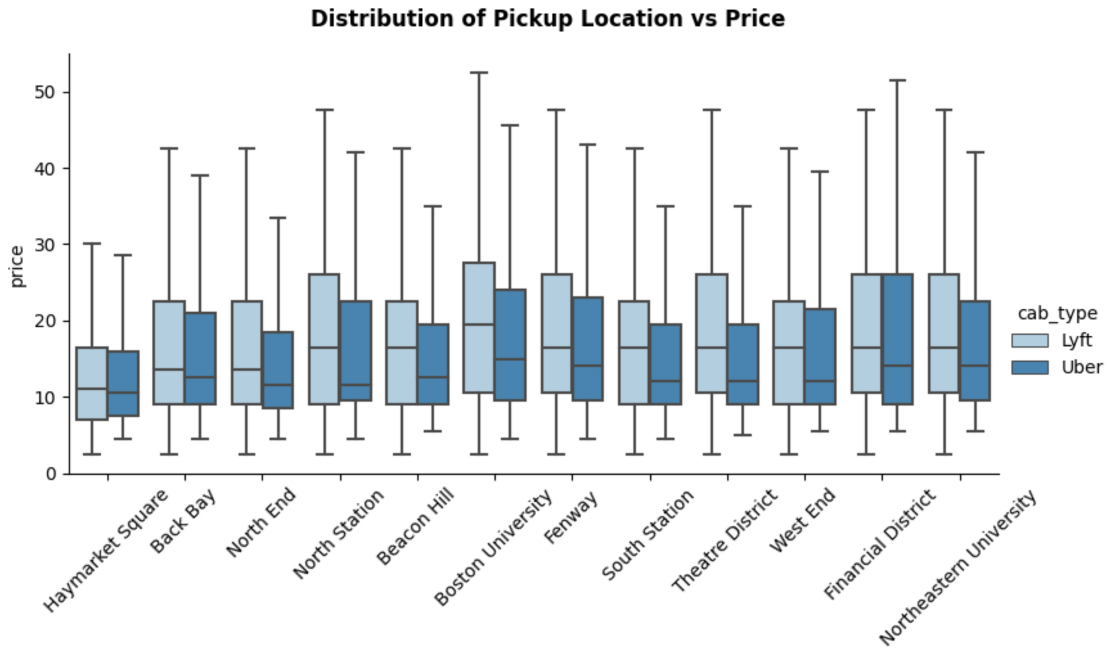
However, when considering larger vehicle types (XL), Uber (UberXL) typically comes with a higher price tag than Lyft (LyftXL).

For a premium service, it's recommended to choose Uber (UberBlack).

3.3 How do prices vary based on different pick-up locations?

It is possible that the pricing fluctuations are correlated with demand. Therefore, we would like to know whether there is a price difference among various pick-up locations. Understanding such variations can shed light on the impact of demand on pricing in different areas.

[ ]:
```
# plotting source against price
sns.catplot(x='source', y='price', data=merged_df, kind='box', hue='cab_type',␣
 ↪sym='', height=4, aspect=2, palette='Blues', dodge=True)
plt.tick_params(axis='x', rotation=45)
plt.suptitle("Distribution of Pickup Location vs Price", y=1.05,␣
 ↪fontweight='bold')
plt.show()
```



From above figure, we are comparing the price differences from various pick up locations.

We observe that prices tend to be higher when starting from places like Boston University, Fenway, and Northeastern University.

One possible reason for this could be high demand in those areas. Additionally, the prices in the Financial District are more varied, which might be related to the distance of the trips.

4 Modeling

Which methods worked best for your problem?

We decided to implement three distinct search methods—GridSearch, RandomizedSearch, and Bayes Search—across four unique models—Linear Regression, Decision Tree Regression, XGBoost Regression and Elastic Net Regression—to achieve hyperparameter tuning. The goal was to identify the optimal models for both Uber and Lyft. To assess the models' performance, we compared the negative root mean squared error for each and selected the model with the highest value. Subsequently, we utilized the chosen model to make predictions on the test dataset. Notably, the best models for both datasets turned out to be XGBoost, utilizing the Bayes Search method.

Uber's best parameters in XGBoost:

1. colsample_bytree: 0.826784
2. max_depth: 5
3. n_estimators: 169

Lyft's best parameters in XGBoost:

1. colsample_bytree: 0.87526
2. max_depth: 7
3. n_estimators: 164

[ ]:
```
# Selecting features
merged_df =␣
↪merged_df[['distance','cab_type','destination','source','price','name','date_time','merge_d

# Creating time period variable and mapping
merged_df['hour'] = merged_df['date_time'].dt.hour.astype(str)
mapping = {
    '6': 'morning','7' : 'morning','8' : 'morning','9' : 'morning',
    '10' : 'noon', '11' : 'noon','12' : 'noon', '13' : 'noon',
    '14' : 'afternoon', '15' : 'afternoon', '16' : 'afternoon', '17' :␣
↪'afternoon',
    '18' : 'evening', '19' : 'evening', '20' : 'evening', '21' : 'evening',
    '22' : 'night', '23' : 'night', '0' : 'night', '1' : 'night',
    '2' : 'night', '3' : 'late_night', '4' : 'late_night', '5' : 'late_night' }
merged_df['time_period'] = merged_df['hour'].replace(mapping)

merged_df.drop(columns=['date_time','merge_date','hour'],axis=1, inplace=True)
merged_df.head(5)
```

[ ]:
```
   distance cab_type    destination           source  price          name  \
0      0.44     Lyft  North Station  Haymarket Square    5.0        Shared
1      0.44     Lyft  North Station  Haymarket Square   11.0           Lux
3      0.44     Lyft  North Station  Haymarket Square   26.0  Lux Black XL
4      0.44     Lyft  North Station  Haymarket Square    9.0       Lyft XL
5      0.44     Lyft  North Station  Haymarket Square   16.5     Lux Black

     temp    clouds  pressure   rain  humidity   wind time_period
0  38.460  0.290000   1022.25  0.000  0.760000   7.68     morning
1  44.065  0.995000   1002.88  0.106  0.895000  12.63       night
3  35.080  0.000000   1013.71  0.000  0.700000   5.25  late_night
4  37.680  0.433333    998.42  0.000  0.706667  11.16  late_night
5  40.780  0.930000   1000.15  0.000  0.790000   7.55     evening
```

[ ]:
```
# Subsetting dataframe into uber and lyft
df_lyft = merged_df[merged_df['cab_type']=='Lyft'].copy()
df_uber = merged_df[merged_df['cab_type']=='Uber'].copy()

# Creating target and features
X_lyft = df_lyft.drop('price',axis=1)
y_lyft = df_lyft['price'].copy()

X_uber = df_uber.drop('price',axis=1)
y_yber = df_uber['price'].copy()
```

[ ]:
```python
# Info for Uber Dataframe
df_uber.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 329140 entries, 12 to 693070
Data columns (total 13 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   distance     329140 non-null  float64
 1   cab_type     329140 non-null  object
 2   destination  329140 non-null  object
 3   source       329140 non-null  object
 4   price        329140 non-null  float64
 5   name         329140 non-null  object
 6   temp         329140 non-null  float64
 7   clouds       329140 non-null  float64
 8   pressure     329140 non-null  float64
 9   rain         329140 non-null  float64
 10  humidity     329140 non-null  float64
 11  wind         329140 non-null  float64
 12  time_period  329140 non-null  object
dtypes: float64(8), object(5)
memory usage: 35.2+ MB
```

[ ]:
```python
# Info for Lyft Dataframe
df_lyft.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 306102 entries, 0 to 693053
Data columns (total 13 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   distance     306102 non-null  float64
 1   cab_type     306102 non-null  object
 2   destination  306102 non-null  object
 3   source       306102 non-null  object
 4   price        306102 non-null  float64
 5   name         306102 non-null  object
 6   temp         306102 non-null  float64
 7   clouds       306102 non-null  float64
 8   pressure     306102 non-null  float64
 9   rain         306102 non-null  float64
 10  humidity     306102 non-null  float64
 11  wind         306102 non-null  float64
 12  time_period  306102 non-null  object
dtypes: float64(8), object(5)
memory usage: 32.7+ MB
```

```
[ ]: # Splitting data into training and testing for Uber and Lyft dataframes
from sklearn.model_selection import train_test_split
X_train_lyft, X_test_lyft, y_train_lyft, y_test_lyft = train_test_split(X_lyft,␣
 ↪y_lyft, test_size=0.2, random_state=42)
X_train_uber, X_test_uber, y_train_uber, y_test_uber = train_test_split(X_uber,␣
 ↪y_yber, test_size=0.2, random_state=42)
```

```
[ ]: # Creating preprocessing pipeline
from sklearn import set_config
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import make_pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder

set_config(display='diagram')

cat_attribs = ["cab_type", "destination", "source", "name", "time_period"]
num_attribs = ["distance", "temp", "clouds", "pressure", "rain", "humidity",␣
 ↪"wind"]

preprocess_pipeline = ColumnTransformer([
        ("cat", OneHotEncoder(drop="first"), cat_attribs),
        ("num", StandardScaler(), num_attribs),])

preprocess_pipeline
```

```
[ ]: ColumnTransformer(transformers=[('cat', OneHotEncoder(drop='first'),
                                  ['cab_type', 'destination', 'source', 'name',
                                   'time_period']),
                                 ('num', StandardScaler(),
                                  ['distance', 'temp', 'clouds', 'pressure',
                                   'rain', 'humidity', 'wind'])])
```

```
[ ]: # Test if it's preprocessing
print(X_train_lyft.shape)
X_train_lyft_prepared = preprocess_pipeline.fit_transform(X_train_lyft)
print(X_train_lyft_prepared.shape)
```

```
(244881, 12)
(244881, 39)
```

```
[ ]: # Test if it's preprocessing
print(X_train_uber.shape)
X_train_uber_prepared = preprocess_pipeline.fit_transform(X_train_uber)
print(X_train_uber_prepared.shape)
```

```
(263312, 12)
```

```
(263312, 39)
```

4.1 Linear Regression

4.1.1 Uber

[ ]:
```
# Linear regression for Uber dataframe
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import cross_val_score

lin_reg_uber = make_pipeline(preprocess_pipeline, LinearRegression())
lin_reg_uber.fit(X_train_uber, y_train_uber)
y_train_predictions_uber = lin_reg_uber.predict(X_train_uber)
lin_cv_rmses = -cross_val_score(lin_reg_uber, X_train_uber, y_train_uber,
                              scoring="neg_root_mean_squared_error", cv=3)
print(f"Average Linear Regression Cross-Validation RMSE: {lin_cv_rmses.mean():.
 ↪0f}")
```

```
Average Linear Regression Cross-Validation RMSE: 2
```

[ ]:
```
# Linear Regression Grid Search for Uber dataframe
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline

param_grid = {
    'linearregression__fit_intercept': [True, False],
    'linearregression__copy_X': [True, False],
    'linearregression__positive': [True, False]
}

lin_uber_grid_search = GridSearchCV(lin_reg_uber, param_grid, cv=3,␣
 ↪scoring='neg_root_mean_squared_error')
lin_uber_grid_search.fit(X_train_uber, y_train_uber)
```

[ ]:
```
GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('columntransformer',
                                        ColumnTransformer(transformers=[('cat',
OneHotEncoder(drop='first'),
['cab_type',
'destination',
'source',
'name',
'time_period']),
                                                                        ('num',
StandardScaler(),
```

```
['distance',
'temp',
'clouds',
'pressure',
'rain',
'humidity',
'wind'])])),
                                        ('linearregression',
                                         LinearRegression())]),
             param_grid={'linearregression__copy_X': [True, False],
                         'linearregression__fit_intercept': [True, False],
                         'linearregression__positive': [True, False]},
             scoring='neg_root_mean_squared_error')
```

[ ]:
```python
# Presenting result
lin_uber_cv = pd.DataFrame(lin_uber_grid_search.cv_results_)
lin_uber_cv.sort_values(by="mean_test_score", ascending=False, inplace=True)
lin_uber_cv.filter(regex = '(^param_|mean_test_score)', axis=1)
```

[ ]:
```
  param_linearregression__copy_X param_linearregression__fit_intercept  \
1                           True                                  True
5                          False                                  True
3                           True                                 False
7                          False                                 False
0                           True                                  True
2                           True                                 False
4                          False                                  True
6                          False                                 False

  param_linearregression__positive  mean_test_score
1                            False        -2.402838
5                            False        -2.402838
3                            False        -2.402838
7                            False        -2.402838
0                             True              NaN
2                             True              NaN
4                             True              NaN
6                             True              NaN
```

[ ]:
```python
# Linear Regression Random Search for Uber dataframe

from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint


lin_uber_rnd_search = RandomizedSearchCV(
    lin_reg_uber, param_distributions=param_grid, n_iter=4, cv=3,
```

```
    scoring='neg_root_mean_squared_error', random_state=42)

lin_uber_rnd_search.fit(X_train_uber, y_train_uber)
```

[ ]:
```
RandomizedSearchCV(cv=3,
                   estimator=Pipeline(steps=[('columntransformer',
ColumnTransformer(transformers=[('cat',
OneHotEncoder(drop='first'),
['cab_type',
'destination',
'source',
'name',
'time_period']),
('num',
StandardScaler(),
['distance',
'temp',
'clouds',
'pressure',
'rain',
'humidity',
'wind'])])),
                                          ('linearregression',
                                           LinearRegression())]),
                   n_iter=4,
                   param_distributions={'linearregression__copy_X': [True,
                                                                      False],
                                        'linearregression__fit_intercept':
[True,
False],
                                        'linearregression__positive': [True,
                                                                       False]},
                   random_state=42, scoring='neg_root_mean_squared_error')
```

[ ]:
```
# Presenting result
lin_uber_rnd_res = pd.DataFrame(lin_uber_rnd_search.cv_results_)
lin_uber_rnd_res.sort_values(by="mean_test_score", ascending=False,␣
↪inplace=True)
lin_uber_rnd_res.filter(regex = '(^param_|mean_test_score)', axis=1)
```

[ ]:
```
  param_linearregression__positive param_linearregression__fit_intercept  \
0                            False                                  True
1                            False                                  True
3                            False                                 False
2                             True                                  True

  param_linearregression__copy_X  mean_test_score
```

```
0                           True        -2.402838
1                          False        -2.402838
3                          False        -2.402838
2                           True              NaN
```

[ ]:
```
# Linear Regression Bayes Search for Uber dataframe
!pip install scikit-optimize
from sklearn.linear_model import LinearRegression
from skopt import BayesSearchCV
from skopt.space import Categorical
```

```
Collecting scikit-optimize
  Downloading scikit_optimize-0.9.0-py2.py3-none-any.whl (100 kB)
                           100.3/100.3

kB 2.4 MB/s eta 0:00:00
Requirement already satisfied: joblib>=0.11 in
/usr/local/lib/python3.10/dist-packages (from scikit-optimize) (1.3.2)
Collecting pyaml>=16.9 (from scikit-optimize)
  Downloading pyaml-23.9.7-py3-none-any.whl (23 kB)
Requirement already satisfied: numpy>=1.13.3 in /usr/local/lib/python3.10/dist-
packages (from scikit-optimize) (1.23.5)
Requirement already satisfied: scipy>=0.19.1 in /usr/local/lib/python3.10/dist-
packages (from scikit-optimize) (1.11.4)
Requirement already satisfied: scikit-learn>=0.20.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-optimize) (1.2.2)
Requirement already satisfied: PyYAML in /usr/local/lib/python3.10/dist-packages
(from pyaml>=16.9->scikit-optimize) (6.0.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.20.0->scikit-
optimize) (3.2.0)
Installing collected packages: pyaml, scikit-optimize
Successfully installed pyaml-23.9.7 scikit-optimize-0.9.0
```

[ ]:
```
sparse_columns = ['cab_type', 'destination', 'source', 'name', 'time_period']

# One-hot encoding categorical features without creating sparse matrices
X_train_uber_selected = X_train_uber[sparse_columns].to_numpy()
uber_bayes_encoder = OneHotEncoder(sparse=False)
X_train_uber_encoded = pd.get_dummies(X_train_uber[sparse_columns])
# Concatenating encoded features with the original dataset
X_train_uber_bayes_final = pd.concat([X_train_uber.
 ↪drop(columns=sparse_columns), X_train_uber_encoded], axis=1)

param_space = {
    'fit_intercept': Categorical([True, False]),
```

```
    'copy_X': Categorical([True, False]),
    'positive': Categorical([True, False])
}

lin_uber_bayesian_search = BayesSearchCV(
    estimator=LinearRegression(),
    search_spaces=param_space,
    n_iter=8,
    cv=3,
    scoring='neg_root_mean_squared_error',
    random_state=42
)

lin_uber_bayesian_search.fit(X_train_uber_bayes_final, y_train_uber)
```

[ ]:
```
BayesSearchCV(cv=3, estimator=LinearRegression(), n_iter=8, random_state=42,
              scoring='neg_root_mean_squared_error',
              search_spaces={'copy_X': Categorical(categories=(True, False),
prior=None),
                             'fit_intercept': Categorical(categories=(True,
False), prior=None),
                             'positive': Categorical(categories=(True, False),
prior=None)})
```

[ ]:
```
# Presenting result
lin_uber_bayes_res = pd.DataFrame(lin_uber_bayesian_search.cv_results_)
lin_uber_bayes_res.sort_values(by="mean_test_score", ascending=False,␣
 ↪inplace=True)
lin_uber_bayes_res.filter(regex = '(^param_|mean_test_score)', axis=1)
```

[ ]:

	param_copy_X	param_fit_intercept	param_positive	mean_test_score
3	True	False	True	-2.402829
4	True	False	True	-2.402829
1	True	True	False	-2.402838
2	False	True	False	-2.402838
5	True	True	False	-2.402838
6	True	True	False	-2.402838
7	True	True	False	-2.402838
0	False	True	True	-2.402908

4.1.2 Lyft

[ ]:
```
# Linear regression for Lyft dataframe

lin_reg_lyft = make_pipeline(preprocess_pipeline, LinearRegression())
lin_reg_lyft.fit(X_train_lyft, y_train_lyft)
y_train_predictions_lyft = lin_reg_lyft.predict(X_train_lyft)
```

```
lin_cv_rmses = -cross_val_score(lin_reg_lyft, X_train_lyft, y_train_lyft,
                                scoring="neg_root_mean_squared_error", cv=3)
print(f"Average Linear Regression Cross-Validation RMSE: {lin_cv_rmses.mean():.
 ↪0f}")
```

```
Average Linear Regression Cross-Validation RMSE: 3
```

[ ]:
```
# Linear Regression Grid Search for Lyft dataframe

param_grid = {
    'linearregression__fit_intercept': [True, False],
    'linearregression__copy_X': [True, False],
    'linearregression__positive': [True, False]
}

lin_lyft_grid_search = GridSearchCV(lin_reg_lyft, param_grid, cv=3,␣
 ↪scoring='neg_root_mean_squared_error')
lin_lyft_grid_search.fit(X_train_lyft, y_train_lyft)
```

[ ]:
```
GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('columntransformer',
                                        ColumnTransformer(transformers=[('cat',
OneHotEncoder(drop='first'),
['cab_type',
'destination',
'source',
'name',
'time_period']),
                                                                        ('num',
StandardScaler(),
['distance',
'temp',
'clouds',
'pressure',
'rain',
'humidity',
'wind'])])),
                                       ('linearregression',
                                        LinearRegression())]),
             param_grid={'linearregression__copy_X': [True, False],
                         'linearregression__fit_intercept': [True, False],
                         'linearregression__positive': [True, False]},
             scoring='neg_root_mean_squared_error')
```

[ ]:
```
# Presenting result
lin_lyft_cv = pd.DataFrame(lin_lyft_grid_search.cv_results_)
lin_lyft_cv.sort_values(by="mean_test_score", ascending=False, inplace=True)
```

```
lin_lyft_cv.filter(regex = '(^param_|mean_test_score)', axis=1)
```

```
[ ]:   param_linearregression__copy_X param_linearregression__fit_intercept  \
1                               True                                  True
5                              False                                  True
3                               True                                 False
7                              False                                 False
0                               True                                  True
2                               True                                 False
4                              False                                  True
6                              False                                 False

  param_linearregression__positive  mean_test_score
1                            False         -3.47924
5                            False         -3.47924
3                            False         -3.47924
7                            False         -3.47924
0                             True              NaN
2                             True              NaN
4                             True              NaN
6                             True              NaN
```

```
[ ]: # Linear Regression Random Search for Lyft dataframe

from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint


lin_lyft_rnd_search = RandomizedSearchCV(
    lin_reg_lyft, param_distributions=param_grid, n_iter=4, cv=3,
    scoring='neg_root_mean_squared_error', random_state=42)

lin_lyft_rnd_search.fit(X_train_lyft, y_train_lyft)
```

```
[ ]: RandomizedSearchCV(cv=3,
                   estimator=Pipeline(steps=[('columntransformer',
ColumnTransformer(transformers=[('cat',
OneHotEncoder(drop='first'),
['cab_type',
'destination',
'source',
'name',
'time_period']),
('num',
StandardScaler(),
['distance',
'temp',
```

```
'clouds',
'pressure',
'rain',
'humidity',
'wind'])])),
                                             ('linearregression',
                                              LinearRegression())]),
                   n_iter=4,
                   param_distributions={'linearregression__copy_X': [True,
                                                                     False],
                                        'linearregression__fit_intercept':
[True,
False],
                                        'linearregression__positive': [True,
                                                                       False]},
                   random_state=42, scoring='neg_root_mean_squared_error')
```

[ ]:
```
# Presenting result
lin_lyft_rnd_res = pd.DataFrame(lin_lyft_rnd_search.cv_results_)
lin_lyft_rnd_res.sort_values(by="mean_test_score", ascending=False,␣
 ↪inplace=True)
lin_lyft_rnd_res.filter(regex = '(^param_|mean_test_score)', axis=1)
```

[ ]:
```
  param_linearregression__positive param_linearregression__fit_intercept  \
0                            False                                  True
1                            False                                  True
3                            False                                 False
2                             True                                  True

  param_linearregression__copy_X  mean_test_score
0                           True         -3.47924
1                          False         -3.47924
3                          False         -3.47924
2                           True              NaN
```

[ ]:
```
# Linear Regression Bayes Search for Lyft dataframe

X_train_lyft_selected = X_train_lyft[sparse_columns].to_numpy()
lyft_bayes_encoder = OneHotEncoder(sparse=False)
X_train_lyft_encoded = pd.get_dummies(X_train_lyft[sparse_columns])
X_train_lyft_bayes_final = pd.concat([X_train_lyft.
 ↪drop(columns=sparse_columns), X_train_lyft_encoded], axis=1)


param_space = {
    'fit_intercept': Categorical([True, False]),
    'copy_X': Categorical([True, False]),
```

```
    'positive': Categorical([True, False])
}

lin_lyft_bayesian_search = BayesSearchCV(
    estimator=LinearRegression(),
    search_spaces=param_space,
    n_iter=8,
    cv=3,
    scoring='neg_root_mean_squared_error',
    random_state=42
)

lin_lyft_bayesian_search.fit(X_train_lyft_bayes_final, y_train_lyft)
```

[ ]:
```
BayesSearchCV(cv=3, estimator=LinearRegression(), n_iter=8, random_state=42,
              scoring='neg_root_mean_squared_error',
              search_spaces={'copy_X': Categorical(categories=(True, False),
prior=None),
                             'fit_intercept': Categorical(categories=(True,
False), prior=None),
                             'positive': Categorical(categories=(True, False),
prior=None)})
```

[ ]:
```
# Presenting result
lin_lyft_bayes_res = pd.DataFrame(lin_lyft_bayesian_search.cv_results_)
lin_lyft_bayes_res.sort_values(by="mean_test_score", ascending=False,␣
↪inplace=True)
lin_lyft_bayes_res.filter(regex = '(^param_|mean_test_score)', axis=1)
```

[ ]:

	param_copy_X	param_fit_intercept	param_positive	mean_test_score
1	True	True	False	-3.479240
2	False	True	False	-3.479240
5	True	True	False	-3.479240
6	True	True	False	-3.479240
7	True	True	False	-3.479240
0	False	True	True	-3.479268
3	True	False	True	-3.523841
4	True	False	True	-3.523841

4.2 DecisionTree Regression

4.2.1 Uber

[ ]:
```
# DecisionTreeRegressor for Uber dataframe
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import cross_val_score
```

```python
from sklearn.pipeline import Pipeline

tree_uber = make_pipeline(preprocess_pipeline,␣
↪DecisionTreeRegressor(random_state=42))

tree_uber.fit(X_train_uber, y_train_uber)
tree_cv_rmses = -cross_val_score(tree_uber, X_train_uber, y_train_uber,
                              scoring="neg_root_mean_squared_error", cv=3)
print(f"Average DecisionTree Regression Cross-Validation RMSE: {tree_cv_rmses.
↪mean():.0f}")
```

```
Average DecisionTree Regression Cross-Validation RMSE: 3
```

[ ]:
```python
# DecisionTreeRegressor Grid Search for Uber dataframe
from sklearn.model_selection import GridSearchCV
import numpy as np

param_grid = {
    'decisiontreeregressor__max_depth' : [10,20],
    'decisiontreeregressor__min_samples_split' : [2,5,10],
    'decisiontreeregressor__min_samples_leaf' : [1,5,10]
}

tree_uber_grid_search = GridSearchCV(tree_uber, param_grid, cv=3,␣
↪scoring='neg_root_mean_squared_error')
tree_uber_grid_search.fit(X_train_uber, y_train_uber)
```

[ ]:
```
GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('columntransformer',
                                        ColumnTransformer(transformers=[('cat',
OneHotEncoder(drop='first'),
['cab_type',
'destination',
'source',
'name',
'time_period']),
                                                                        ('num',
StandardScaler(),
['distance',
'temp',
'clouds',
'pressure',
'rain',
'humidity',
'wind'])])),
                                       ('decisiontreeregressor',
DecisionTreeRegressor(random_state=42))]),
```

```
              param_grid={'decisiontreeregressor__max_depth': [10, 20],
                          'decisiontreeregressor__min_samples_leaf': [1, 5, 10],
                          'decisiontreeregressor__min_samples_split': [2, 5,
                                                                       10]},
              scoring='neg_root_mean_squared_error')
```

[ ]:
```
# Presenting result
tree_uber_cv = pd.DataFrame(tree_uber_grid_search.cv_results_)
tree_uber_cv.sort_values(by="mean_test_score", ascending=False, inplace=True)
tree_uber_cv.filter(regex = '(^param_|mean_test_score)', axis=1).head(10)
```

[ ]:
```
   param_decisiontreeregressor__max_depth  \
6                                      10
7                                      10
8                                      10
3                                      10
4                                      10
5                                      10
2                                      10
1                                      10
0                                      10
15                                     20

   param_decisiontreeregressor__min_samples_leaf  \
6                                             10
7                                             10
8                                             10
3                                              5
4                                              5
5                                              5
2                                              1
1                                              1
0                                              1
15                                            10

   param_decisiontreeregressor__min_samples_split  mean_test_score
6                                               2        -1.935140
7                                               5        -1.935140
8                                              10        -1.935140
3                                               2        -1.938275
4                                               5        -1.938275
5                                              10        -1.938275
2                                              10        -1.944237
1                                               5        -1.946858
0                                               2        -1.958493
15                                              2        -2.023783
```

[ ]:
```python
# DecisionTreeRegressor Random Search for Uber dataframe
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint

param_grid = {
    'decisiontreeregressor__max_depth' : randint(10,20),
    'decisiontreeregressor__min_samples_split' : randint(2,20),
    'decisiontreeregressor__min_samples_leaf' : randint(1,20)
}

tree_uber_rnd_search = RandomizedSearchCV(
    tree_uber, param_grid, n_iter=10, cv=3,
    scoring='neg_root_mean_squared_error', random_state=42)

tree_uber_rnd_search.fit(X_train_uber, y_train_uber)
```

[ ]:
```
RandomizedSearchCV(cv=3,
                   estimator=Pipeline(steps=[('columntransformer',
ColumnTransformer(transformers=[('cat',
OneHotEncoder(drop='first'),
['cab_type',
'destination',
'source',
'name',
'time_period']),
('num',
StandardScaler(),
['distance',
'temp',
'clouds',
'pressure',
'rain',
'humidity',
'wind'])])),
                                             ('decisiontreeregressor',
DecisionTreeRegressor(random_state=4…
                   param_distributions={'decisiontreeregressor__max_depth':
<scipy.stats._distn_infrastructure.rv_discrete_frozen object at 0x7e06596ff3d0>,
'decisiontreeregressor__min_samples_leaf':
<scipy.stats._distn_infrastructure.rv_discrete_frozen object at 0x7e065974d990>,
'decisiontreeregressor__min_samples_split':
<scipy.stats._distn_infrastructure.rv_discrete_frozen object at
0x7e065969d720>},
                   random_state=42, scoring='neg_root_mean_squared_error')
```

[ ]:
```python
# Presenting result
tree_uber_rnd_res = pd.DataFrame(tree_uber_rnd_search.cv_results_)
```

```
tree_uber_rnd_res.sort_values(by="mean_test_score", ascending=False,␣
 ↪inplace=True)
tree_uber_rnd_res.filter(regex = '(^param_|mean_test_score)', axis=1).head(10)
```

[ ]:
```
  param_decisiontreeregressor__max_depth  \
8                                     12
9                                     14
5                                     11
0                                     16
7                                     19
4                                     17
6                                     19
1                                     17
2                                     17
3                                     17

  param_decisiontreeregressor__min_samples_leaf  \
8                                            12
9                                            19
5                                             1
0                                            15
7                                            16
4                                            12
6                                            12
1                                             7
2                                             4
3                                             3

  param_decisiontreeregressor__min_samples_split  mean_test_score
8                                              4        -1.933138
9                                              8        -1.937784
5                                             13        -1.944010
0                                             12        -1.959175
7                                             16        -1.980236
4                                              7        -1.981772
6                                             18        -2.001345
1                                             12        -2.011283
2                                              9        -2.041862
3                                              3        -2.070410
```

[ ]:
```
# Install necessary libraries
!pip install scikit-optimize
from skopt import BayesSearchCV
from skopt.space import Categorical
```

```
Requirement already satisfied: scikit-optimize in
/usr/local/lib/python3.10/dist-packages (0.9.0)
```

```
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.10/dist-
packages (from scikit-optimize) (1.3.2)
Requirement already satisfied: pyaml>=16.9 in /usr/local/lib/python3.10/dist-
packages (from scikit-optimize) (23.9.7)
Requirement already satisfied: numpy>=1.13.3 in /usr/local/lib/python3.10/dist-
packages (from scikit-optimize) (1.23.5)
Requirement already satisfied: scipy>=0.19.1 in /usr/local/lib/python3.10/dist-
packages (from scikit-optimize) (1.11.4)
Requirement already satisfied: scikit-learn>=0.20.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-optimize) (1.2.2)
Requirement already satisfied: PyYAML in /usr/local/lib/python3.10/dist-packages
(from pyaml>=16.9->scikit-optimize) (6.0.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.20.0->scikit-
optimize) (3.2.0)
```

[ ]:
```
# DecisionTreeRegressor Bayes Search for Uber dataframe
param_grid = {
    'decisiontreeregressor__max_depth' : [10,20],
    'decisiontreeregressor__min_samples_split' : [2,5,10],
    'decisiontreeregressor__min_samples_leaf' : [1,5,10]
}

tree_uber_bayesian_search = BayesSearchCV(
    estimator=tree_uber,
    search_spaces=param_grid,
    n_iter=10,
    cv=3,
    scoring='neg_root_mean_squared_error',
    random_state=42
)

tree_uber_bayesian_search.fit(X_train_uber, y_train_uber)
```

[ ]:
```
BayesSearchCV(cv=3,
              estimator=Pipeline(steps=[('columntransformer',
                                          ColumnTransformer(transformers=[('cat',
OneHotEncoder(drop='first'),
['cab_type',
'destination',
'source',
'name',
'time_period']),
                                                                          ('num',
StandardScaler(),
['distance',
'temp',
```

```
'clouds',
'pressure',
'rain',
'humidity',
'wind'])])),
                                        ('decisiontreeregressor',
DecisionTreeRegressor(random_state=42))]),
              n_iter=10, random_state=42, scoring='neg_root_mean_squared_error',
              search_spaces={'decisiontreeregressor__max_depth': [10, 20],
                             'decisiontreeregressor__min_samples_leaf': [1, 5,
                                                                          10],
                             'decisiontreeregressor__min_samples_split': [2, 5,
                                                                           10]})
```

[ ]:
```
# Presenting result
tree_uber_bayes_res = pd.DataFrame(tree_uber_bayesian_search.cv_results_)
tree_uber_bayes_res.sort_values(by="mean_test_score", ascending=False,␣
 ↪inplace=True)
tree_uber_bayes_res.filter(regex = '(^param_|mean_test_score)', axis=1).head(10)
```

[ ]:
```
  param_decisiontreeregressor__max_depth  \
9                                      10
2                                      14
7                                      15
0                                      14
6                                      16
5                                      17
1                                      18
4                                      18
8                                      20
3                                      18

  param_decisiontreeregressor__min_samples_leaf  \
9                                             10
2                                             10
7                                             10
0                                              5
6                                             10
5                                             10
1                                             10
4                                              5
8                                              5
3                                              1

  param_decisiontreeregressor__min_samples_split  mean_test_score
9                                              5        -1.935140
2                                              2        -1.953656
```

```
7                                              5      -1.965383
0                                             10      -1.971660
6                                              5      -1.979480
5                                              2      -1.992081
1                                              5      -2.003567
4                                              5      -2.047339
8                                             10      -2.082457
3                                              5      -2.171583
```

4.2.2 Lyft

[ ]:
```python
# DecisionTreeRegressor for Lyft dataframe
tree_lyft = make_pipeline(preprocess_pipeline,␣
 ↪DecisionTreeRegressor(random_state=42))
tree_lyft.fit(X_train_lyft, y_train_lyft)

tree_cv_rmses = -cross_val_score(tree_lyft, X_train_lyft, y_train_lyft,
                              scoring="neg_root_mean_squared_error", cv=3)
print(f"Average DecisionTree Regression Cross-Validation RMSE: {tree_cv_rmses.
 ↪mean():.0f}")
```

```
Average DecisionTree Regression Cross-Validation RMSE: 4
```

[ ]:
```python
# DecisionTreeRegressor Grid Search for Lyft dataframe
from sklearn.model_selection import GridSearchCV
import numpy as np

param_grid = {
    'decisiontreeregressor__max_depth' : [10,20],
    'decisiontreeregressor__min_samples_split' : [2,5,10],
    'decisiontreeregressor__min_samples_leaf' : [1,5,10]
}

tree_lyft_grid_search = GridSearchCV(tree_lyft, param_grid, cv=3,␣
 ↪scoring='neg_root_mean_squared_error')
tree_lyft_grid_search.fit(X_train_lyft, y_train_lyft)
```

[ ]:
```
GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('columntransformer',
                                        ColumnTransformer(transformers=[('cat',
OneHotEncoder(drop='first'),
['cab_type',
'destination',
'source',
'name',
'time_period']),
                                                                        ('num',
```

```
StandardScaler(),
['distance',
'temp',
'clouds',
'pressure',
'rain',
'humidity',
'wind'])])),
                                        ('decisiontreeregressor',
DecisionTreeRegressor(random_state=42))]),
             param_grid={'decisiontreeregressor__max_depth': [10, 20],
                         'decisiontreeregressor__min_samples_leaf': [1, 5, 10],
                         'decisiontreeregressor__min_samples_split': [2, 5,
                                                                      10]},
             scoring='neg_root_mean_squared_error')
```

[ ]:
```
# Presenting result
tree_lyft_cv = pd.DataFrame(tree_lyft_grid_search.cv_results_)
tree_lyft_cv.sort_values(by="mean_test_score", ascending=False, inplace=True)
tree_lyft_cv.filter(regex = '(^param_|mean_test_score)', axis=1).head(10)
```

[ ]:
```
   param_decisiontreeregressor__max_depth  \
6                                       10
7                                       10
8                                       10
3                                       10
4                                       10
5                                       10
2                                       10
1                                       10
0                                       10
15                                      20

   param_decisiontreeregressor__min_samples_leaf  \
6                                              10
7                                              10
8                                              10
3                                               5
4                                               5
5                                               5
2                                               1
1                                               1
0                                               1
15                                             10

   param_decisiontreeregressor__min_samples_split  mean_test_score
6                                               2        -3.109589
```

```
7                                              5        -3.109589
8                                             10        -3.109589
3                                              2        -3.121271
4                                              5        -3.121271
5                                             10        -3.121271
2                                             10        -3.143029
1                                              5        -3.152581
0                                              2        -3.162694
15                                             2        -3.275394
```

[ ]:
```python
# DecisionTreeRegressor Random Search for Lyft dataframe
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint

param_grid = {
    'decisiontreeregressor__max_depth' : randint(10,20),
    'decisiontreeregressor__min_samples_split' : randint(2,20),
    'decisiontreeregressor__min_samples_leaf' : randint(1,20)
}

tree_lyft_rnd_search = RandomizedSearchCV(
    tree_lyft, param_grid, n_iter=10, cv=3,
    scoring='neg_root_mean_squared_error', random_state=42)

tree_lyft_rnd_search.fit(X_train_lyft, y_train_lyft)
```

[ ]:
```
RandomizedSearchCV(cv=3,
                   estimator=Pipeline(steps=[('columntransformer',
ColumnTransformer(transformers=[('cat',
OneHotEncoder(drop='first'),
['cab_type',
'destination',
'source',
'name',
'time_period']),
('num',
StandardScaler(),
['distance',
'temp',
'clouds',
'pressure',
'rain',
'humidity',
'wind'])])),
                                             ('decisiontreeregressor',
DecisionTreeRegressor(random_state=4…
                   param_distributions={'decisiontreeregressor__max_depth':
```

```
<scipy.stats._distn_infrastructure.rv_discrete_frozen object at 0x7e06596fcaf0>,
'decisiontreeregressor__min_samples_leaf':
<scipy.stats._distn_infrastructure.rv_discrete_frozen object at 0x7e0659768850>,
'decisiontreeregressor__min_samples_split':
<scipy.stats._distn_infrastructure.rv_discrete_frozen object at
0x7e065974f160>},
                   random_state=42, scoring='neg_root_mean_squared_error')
```

[ ]:
```
# Presenting result
tree_lyft_rnd_res = pd.DataFrame(tree_lyft_rnd_search.cv_results_)
tree_lyft_rnd_res.sort_values(by="mean_test_score", ascending=False,␣
 ↪inplace=True)
tree_lyft_rnd_res.filter(regex = '(^param_|mean_test_score)', axis=1).head(10)
```

[ ]:
```
  param_decisiontreeregressor__max_depth  \
9                                     14
8                                     12
5                                     11
0                                     16
7                                     19
4                                     17
6                                     19
1                                     17
2                                     17
3                                     17

  param_decisiontreeregressor__min_samples_leaf  \
9                                            19
8                                            12
5                                             1
0                                            15
7                                            16
4                                            12
6                                            12
1                                             7
2                                             4
3                                             3

  param_decisiontreeregressor__min_samples_split  mean_test_score
9                                              8        -3.123658
8                                              4        -3.129115
5                                             13        -3.155909
0                                             12        -3.175492
7                                             16        -3.200898
4                                              7        -3.218256
6                                             18        -3.241673
1                                             12        -3.285188
```

```
2                                               9         -3.374799
3                                               3         -3.442527
```

[ ]:
```
# Install necessary libraries
!pip install scikit-optimize
from skopt import BayesSearchCV
from skopt.space import Categorical
```

```
Requirement already satisfied: scikit-optimize in
/usr/local/lib/python3.10/dist-packages (0.9.0)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.10/dist-
packages (from scikit-optimize) (1.3.2)
Requirement already satisfied: pyaml>=16.9 in /usr/local/lib/python3.10/dist-
packages (from scikit-optimize) (23.9.7)
Requirement already satisfied: numpy>=1.13.3 in /usr/local/lib/python3.10/dist-
packages (from scikit-optimize) (1.23.5)
Requirement already satisfied: scipy>=0.19.1 in /usr/local/lib/python3.10/dist-
packages (from scikit-optimize) (1.11.4)
Requirement already satisfied: scikit-learn>=0.20.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-optimize) (1.2.2)
Requirement already satisfied: PyYAML in /usr/local/lib/python3.10/dist-packages
(from pyaml>=16.9->scikit-optimize) (6.0.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.20.0->scikit-
optimize) (3.2.0)
```

[ ]:
```
# DecisionTreeRegressor Bayes Search for Lyft dataframe
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import cross_val_score
from sklearn.pipeline import Pipeline
from scipy.stats import randint

param_grid = {
    'decisiontreeregressor__max_depth' : [10,20],
    'decisiontreeregressor__min_samples_split' : [2,5,10],
    'decisiontreeregressor__min_samples_leaf' : [1,5,10]
}

tree_lyft_bayesian_search = BayesSearchCV(
    estimator=tree_lyft,
    search_spaces=param_grid,
    n_iter=10,
    cv=3,
    scoring='neg_root_mean_squared_error',
    random_state=42
)
```

```
tree_lyft_bayesian_search.fit(X_train_lyft, y_train_lyft)
```

[ ]:
```
BayesSearchCV(cv=3,
              estimator=Pipeline(steps=[('columntransformer',
                                         ColumnTransformer(transformers=[('cat',
OneHotEncoder(drop='first'),
['cab_type',
'destination',
'source',
'name',
'time_period']),
                                                                         ('num',
StandardScaler(),
['distance',
'temp',
'clouds',
'pressure',
'rain',
'humidity',
'wind'])])),
                                        ('decisiontreeregressor',
DecisionTreeRegressor(random_state=42))]),
              n_iter=10, random_state=42, scoring='neg_root_mean_squared_error',
              search_spaces={'decisiontreeregressor__max_depth': [10, 20],
                             'decisiontreeregressor__min_samples_leaf': [1, 5,
                                                                          10],
                             'decisiontreeregressor__min_samples_split': [2, 5,
                                                                           10]})
```

[ ]:
```
# Presenting result
tree_lyft_bayes_res = pd.DataFrame(tree_lyft_bayesian_search.cv_results_)
tree_lyft_bayes_res.sort_values(by="mean_test_score", ascending=False,␣
 ↪inplace=True)
tree_lyft_bayes_res.filter(regex = '(^param_|mean_test_score)', axis=1).head(10)
```

[ ]:
```
  param_decisiontreeregressor__max_depth  \
9                                     10
2                                     14
7                                     15
6                                     16
5                                     17
0                                     14
1                                     18
4                                     18
8                                     20
3                                     18
```

```
  param_decisiontreeregressor__min_samples_leaf  \
9                                             10
2                                             10
7                                             10
6                                             10
5                                             10
0                                              5
1                                             10
4                                              5
8                                              5
3                                              1

  param_decisiontreeregressor__min_samples_split  mean_test_score
9                                              5        -3.109589
2                                              2        -3.174279
7                                              5        -3.196858
6                                              5        -3.217336
5                                              2        -3.235908
0                                             10        -3.238037
1                                              5        -3.250482
4                                              5        -3.377004
8                                             10        -3.425158
3                                              5        -3.675220
```

4.3 Elastic Net Regression

4.3.1 Uber

[ ]:
```python
# Elastic Net regression for Uber dataframe
from sklearn.linear_model import ElasticNet
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import cross_val_score

elastic_net_uber = make_pipeline(preprocess_pipeline, ElasticNet())
elastic_net_uber.fit(X_train_uber, y_train_uber)
elastic_net_cv_rmses = -cross_val_score(elastic_net_uber, X_train_uber,␣
 ↪y_train_uber,
                              scoring="neg_root_mean_squared_error", cv=3)
print(f"Average Elastic Net Regression Cross-Validation RMSE:␣
 ↪{elastic_net_cv_rmses.mean():.0f}")
```

```
Average Elastic Net Regression Cross-Validation RMSE: 7
```

[ ]:
```python
# Elastic Net Regression Grid Search for Uber dataframe
from sklearn.model_selection import GridSearchCV
```

```python
from sklearn.pipeline import Pipeline

param_grid = {
    'elasticnet__alpha': [0.1, 0.5, 1.0],
    'elasticnet__l1_ratio': [0.1, 0.5, 0.9],
    'elasticnet__fit_intercept': [True, False],
    'elasticnet__positive': [True, False],}

elastic_net_uber = make_pipeline(preprocess_pipeline, ElasticNet())
elastic_net_grid_search = GridSearchCV(elastic_net_uber, param_grid, cv=3,
 ↪scoring='neg_root_mean_squared_error')
elastic_net_grid_search.fit(X_train_uber, y_train_uber)
```

[ ]:
```
GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('columntransformer',
                                        ColumnTransformer(transformers=[('cat',
OneHotEncoder(drop='first'),
['cab_type',
'destination',
'source',
'name',
'time_period']),
                                                                                ('num',
StandardScaler(),
['distance',
'temp',
'clouds',
'pressure',
'rain',
'humidity',
'wind'])])),
                                       ('elasticnet', ElasticNet())]),
             param_grid={'elasticnet__alpha': [0.1, 0.5, 1.0],
                         'elasticnet__fit_intercept': [True, False],
                         'elasticnet__l1_ratio': [0.1, 0.5, 0.9],
                         'elasticnet__positive': [True, False]},
             scoring='neg_root_mean_squared_error')
```

[ ]:
```python
# Presenting result
elastic_net_uber_cv = pd.DataFrame(elastic_net_grid_search.cv_results_)
elastic_net_uber_cv.sort_values(by="mean_test_score", ascending=False,
 ↪inplace=True)
elastic_net_uber_cv.filter(regex='(^param_|mean_test_score)', axis=1).head(10)
```

[ ]:
```
   param_elasticnet__alpha param_elasticnet__fit_intercept  \
5                      0.1                            True
3                      0.1                            True
```

```
1                       0.1                            True
17                      0.5                            True
4                       0.1                            True
2                       0.1                            True
11                      0.1                           False
10                      0.1                           False
0                       0.1                            True
16                      0.5                            True

   param_elasticnet__l1_ratio param_elasticnet__positive  mean_test_score
5                         0.9                      False        -2.773754
3                         0.5                      False        -3.413798
1                         0.1                      False        -3.928199
17                        0.9                      False        -4.622299
4                         0.9                       True        -4.695244
2                         0.5                       True        -5.032953
11                        0.9                      False        -5.065001
10                        0.9                       True        -5.282374
0                         0.1                       True        -5.374240
16                        0.9                       True        -5.484940
```

[ ]:
```python
# Elastic Net Regression Random Search for Uber dataframe
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import uniform

param_distribs = {
    'elasticnet__alpha': uniform(0, 1),
    'elasticnet__l1_ratio': uniform(0, 1),
    'elasticnet__fit_intercept': [True, False],
    'elasticnet__positive': [True, False]}

elastic_net_rnd_search = RandomizedSearchCV(
    elastic_net_uber, param_distributions=param_distribs, n_iter=10, cv=3,
    scoring='neg_root_mean_squared_error', random_state=42)

elastic_net_rnd_search.fit(X_train_uber, y_train_uber)
```

[ ]:
```
RandomizedSearchCV(cv=3,
                   estimator=Pipeline(steps=[('columntransformer',
ColumnTransformer(transformers=[('cat',
OneHotEncoder(drop='first'),
['cab_type',
'destination',
'source',
'name',
'time_period']),
('num',
```

```
StandardScaler(),
['distance',
'temp',
'clouds',
'pressure',
'rain',
'humidity',
'wind'])])),
                                                  ('elasticnet', ElasticNet())]),
                   param_distributions={'elasticnet__alpha':
<scipy.stats._distn_infrastructure.rv_continuous_frozen object at
0x7e06595be920>,
                                        'elasticnet__fit_intercept': [True,
                                                                      False],
                                        'elasticnet__l1_ratio':
<scipy.stats._distn_infrastructure.rv_continuous_frozen object at
0x7e065976acb0>,
                                        'elasticnet__positive': [True, False]},
                   random_state=42, scoring='neg_root_mean_squared_error')
```

[ ]:
```python
# Presenting result
elastic_net_uber_rnd_res = pd.DataFrame(elastic_net_rnd_search.cv_results_)
elastic_net_uber_rnd_res.sort_values(by="mean_test_score", ascending=False,
 ↪inplace=True)
elastic_net_uber_rnd_res.filter(regex='^(param_|mean_test_score)').head(10)
```

[ ]:
```
  param_elasticnet__alpha param_elasticnet__fit_intercept  \
2                0.058084                           False
7                0.139494                           False
8                 0.45607                            True
0                 0.37454                            True
6                0.431945                            True
5                0.183405                           False
1                0.598658                            True
9                0.514234                           False
3                0.708073                           False
4                0.832443                           False

  param_elasticnet__l1_ratio param_elasticnet__positive  mean_test_score
2                   0.333709                      False        -5.316421
7                   0.973756                       True        -5.386674
8                   0.618386                      False        -5.438361
0                   0.183435                      False        -5.849585
6                   0.524775                       True        -6.352243
5                   0.611653                       True        -6.481434
1                   0.445833                       True        -6.832557
9                   0.466763                       True       -10.021694
```

```
3                    0.056412                      False       -12.272700
4                    0.000779                      False       -12.892390
```

[ ]:
```python
# Elastic Net Regression Bayes Search for Uber dataframe
sparse_columns = ['cab_type', 'destination', 'source', 'name', 'time_period']

X_train_uber_selected = X_train_uber[sparse_columns].to_numpy()
uber_bayes_encoder = OneHotEncoder(sparse=False)
X_train_uber_encoded = pd.get_dummies(X_train_uber[sparse_columns])
X_train_uber_bayes_final = pd.concat([X_train_uber.
 ↪drop(columns=sparse_columns), X_train_uber_encoded], axis=1)

param_distribs = {
    'alpha': (0.01, 1.0, 'uniform'),
    'l1_ratio': (0.01, 1.0, 'uniform'),
    'fit_intercept': [True, False],
    'positive': [True, False]}

elastic_net_bayes_search = BayesSearchCV(
    estimator=ElasticNet(),
    search_spaces=param_distribs,
    n_iter=10, cv=3,
    scoring='neg_root_mean_squared_error', random_state=42)

elastic_net_bayes_search.fit(X_train_uber_bayes_final, y_train_uber)
```

[ ]:
```
BayesSearchCV(cv=3, estimator=ElasticNet(), n_iter=10, random_state=42,
              scoring='neg_root_mean_squared_error',
              search_spaces={'alpha': (0.01, 1.0, 'uniform'),
                             'fit_intercept': [True, False],
                             'l1_ratio': (0.01, 1.0, 'uniform'),
                             'positive': [True, False]})
```

[ ]:
```python
# Presenting result
elastic_net_uber_bayes_search = pd.DataFrame(elastic_net_bayes_search.
 ↪cv_results_)
elastic_net_uber_bayes_search.sort_values(by="mean_test_score",␣
 ↪ascending=False, inplace=True)
elastic_net_uber_bayes_search.filter(regex='^(param_|mean_test_score)').head(10)
```

[ ]:
```
  param_alpha param_fit_intercept param_l1_ratio param_positive  \
9    0.013594                True        0.74387          False
0    0.416003                True       0.933539          False
2    0.450384                True       0.113811          False
8    0.955923                True       0.872935          False
7    0.547969                True       0.501502           True
5    0.736688                True       0.171971          False
```

```
6    0.620909                 True        0.365433           True
3    0.814272                False        0.602067           True
4    0.801558                False        0.531354           True
1    0.839014                 True        0.310376           True

   mean_test_score
9        -2.417090
0        -3.780388
2        -6.048618
8        -6.294131
7        -6.410722
5        -6.702840
6        -6.768686
3        -6.811925
4        -6.893178
1        -7.158599
```

4.3.2 Lyft

[ ]:
```python
# Elastic Net regression for Lyft dataframe

elastic_net_lyft = make_pipeline(preprocess_pipeline, ElasticNet())
elastic_net_lyft.fit(X_train_lyft, y_train_lyft)
y_train_predictions_lyft = elastic_net_lyft.predict(X_train_lyft)
elastic_net_cv_rmses = -cross_val_score(elastic_net_lyft, X_train_lyft,␣
↪y_train_lyft,
                              scoring="neg_root_mean_squared_error", cv=3)
print(f"Average Elastic Net Regression Cross-Validation RMSE:␣
↪{elastic_net_cv_rmses.mean():.0f}")
```

```
Average Elastic Net Regression Cross-Validation RMSE: 8
```

[ ]:
```python
# Elastic Net Regression Grid Search for Lyft dataframe

param_grid = {
    'elasticnet__alpha': [0.1, 0.5, 1.0],
    'elasticnet__l1_ratio': [0.1, 0.5, 0.9],
    'elasticnet__fit_intercept': [True, False],
    'elasticnet__positive': [True, False],}

elastic_net_lyft = make_pipeline(preprocess_pipeline, ElasticNet())
elastic_net_grid_search = GridSearchCV(elastic_net_lyft, param_grid, cv=3,␣
↪scoring='neg_root_mean_squared_error')
elastic_net_grid_search.fit(X_train_lyft, y_train_lyft)
```

[ ]:
```
GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('columntransformer',
                                        ColumnTransformer(transformers=[('cat',
OneHotEncoder(drop='first'),
['cab_type',
'destination',
'source',
'name',
'time_period']),
                                                                        ('num',
StandardScaler(),
['distance',
'temp',
'clouds',
'pressure',
'rain',
'humidity',
'wind'])])),
                                       ('elasticnet', ElasticNet())]),
             param_grid={'elasticnet__alpha': [0.1, 0.5, 1.0],
                         'elasticnet__fit_intercept': [True, False],
                         'elasticnet__l1_ratio': [0.1, 0.5, 0.9],
                         'elasticnet__positive': [True, False]},
             scoring='neg_root_mean_squared_error')
```

[ ]:
```
# Presenting result
elastic_net_lyft_cv = pd.DataFrame(elastic_net_grid_search.cv_results_)
elastic_net_lyft_cv.sort_values(by="mean_test_score", ascending=False,␣
 ↪inplace=True)
elastic_net_lyft_cv.filter(regex='(^param_|mean_test_score)', axis=1).head(10)
```

[ ]:
```
   param_elasticnet__alpha param_elasticnet__fit_intercept  \
5                      0.1                            True
3                      0.1                            True
1                      0.1                            True
4                      0.1                            True
11                     0.1                           False
17                     0.5                            True
10                     0.1                           False
2                      0.1                            True
9                      0.1                           False
8                      0.1                           False

   param_elasticnet__l1_ratio param_elasticnet__positive  mean_test_score
5                         0.9                      False        -3.643614
3                         0.5                      False        -4.146584
1                         0.1                      False        -4.663989
```

4	0.9	True	-5.081580
11	0.9	False	-5.118657
17	0.9	False	-5.144882
10	0.9	True	-5.497436
2	0.5	True	-5.663903
9	0.5	False	-5.842750
8	0.5	True	-6.127570

[ ]:
```
# Elastic Net Regression Random Search for Lyft dataframe

param_distribs = {
    'elasticnet__alpha': uniform(0, 1),
    'elasticnet__l1_ratio': uniform(0, 1),
    'elasticnet__fit_intercept': [True, False],
    'elasticnet__positive': [True, False]}

elastic_net_rnd_search = RandomizedSearchCV(
    elastic_net_lyft, param_distributions=param_distribs, n_iter=10, cv=3,
    scoring='neg_root_mean_squared_error', random_state=42)

elastic_net_rnd_search.fit(X_train_lyft, y_train_lyft)
```

[ ]:
```
RandomizedSearchCV(cv=3,
                   estimator=Pipeline(steps=[('columntransformer',
ColumnTransformer(transformers=[('cat',
OneHotEncoder(drop='first'),
['cab_type',
'destination',
'source',
'name',
'time_period']),
('num',
StandardScaler(),
['distance',
'temp',
'clouds',
'pressure',
'rain',
'humidity',
'wind'])])),
                                             ('elasticnet', ElasticNet())]),
                   param_distributions={'elasticnet__alpha':
<scipy.stats._distn_infrastructure.rv_continuous_frozen object at
0x7e06595bc7c0>,
                                        'elasticnet__fit_intercept': [True,
                                                                      False],
                                        'elasticnet__l1_ratio':
```

```
<scipy.stats._distn_infrastructure.rv_continuous_frozen object at
0x7e0659612110>,
                                        'elasticnet__positive': [True, False]},
                   random_state=42, scoring='neg_root_mean_squared_error')
```

[ ]:
```
# Presenting result
elastic_net_lyft_rnd_res = pd.DataFrame(elastic_net_rnd_search.cv_results_)
elastic_net_lyft_rnd_res.sort_values(by="mean_test_score", ascending=False,␣
 ↪inplace=True)
elastic_net_lyft_rnd_res.filter(regex='^(param_|mean_test_score)').head(10)
```

[ ]:
```
  param_elasticnet__alpha param_elasticnet__fit_intercept  \
2                0.058084                            False
7                0.139494                            False
8                 0.45607                             True
0                 0.37454                             True
5                0.183405                            False
6                0.431945                             True
1                0.598658                             True
9                0.514234                            False
3                0.708073                            False
4                0.832443                            False

  param_elasticnet__l1_ratio param_elasticnet__positive  mean_test_score
2                   0.333709                      False        -5.401231
7                   0.973756                       True        -5.634315
8                   0.618386                      False        -6.244404
0                   0.183435                      False        -6.774094
5                   0.611653                       True        -6.793337
6                   0.524775                       True        -7.433733
1                   0.445833                       True        -8.012347
9                   0.466763                       True       -10.750987
3                   0.056412                      False       -13.474418
4                   0.000779                      False       -14.204772
```

[ ]:
```
# Elastic Net Regression Bayes Search for Lyft dataframe
X_train_lyft_selected = X_train_lyft[sparse_columns].to_numpy()
lyft_bayes_encoder = OneHotEncoder(sparse=False)
X_train_lyft_encoded = pd.get_dummies(X_train_lyft[sparse_columns])
X_train_lyft_bayes_final = pd.concat([X_train_lyft.
 ↪drop(columns=sparse_columns), X_train_lyft_encoded], axis=1)

param_distribs = {
    'alpha': (0.01, 1.0, 'uniform'),
    'l1_ratio': (0.01, 1.0, 'uniform'),
    'fit_intercept': [True, False],
    'positive': [True, False]}
```

```
elastic_net_bayes_search = BayesSearchCV(
    estimator=ElasticNet(),
    search_spaces=param_distribs,
    n_iter=10, cv=3,
    scoring='neg_root_mean_squared_error', random_state=42)

elastic_net_bayes_search.fit(X_train_lyft_bayes_final, y_train_lyft)
```

[ ]:
```
BayesSearchCV(cv=3, estimator=ElasticNet(), n_iter=10, random_state=42,
              scoring='neg_root_mean_squared_error',
              search_spaces={'alpha': (0.01, 1.0, 'uniform'),
                             'fit_intercept': [True, False],
                             'l1_ratio': (0.01, 1.0, 'uniform'),
                             'positive': [True, False]})
```

[ ]:
```
# Presenting result
elastic_net_lyft_bayes_search = pd.DataFrame(elastic_net_bayes_search.
 ↪cv_results_)
elastic_net_lyft_bayes_search.sort_values(by="mean_test_score",␣
 ↪ascending=False, inplace=True)
elastic_net_lyft_bayes_search.filter(regex='^(param_|mean_test_score)').head(10)
```

[ ]:

	param_alpha	param_fit_intercept	param_l1_ratio	param_positive
9	0.013594	True	0.74387	False
0	0.416003	True	0.933539	False
8	0.955923	True	0.872935	False
2	0.450384	True	0.113811	False
7	0.547969	True	0.501502	True
5	0.736688	True	0.171971	False
6	0.620909	True	0.365433	True
3	0.814272	False	0.602067	True
4	0.801558	False	0.531354	True
1	0.839014	True	0.310376	True

	mean_test_score
9	-3.491303
0	-4.584596
8	-7.000939
2	-7.170831
7	-7.796131
5	-7.880016
6	-8.139924
3	-8.169614
4	-8.252276
1	-8.520885

4.4 XGBoost Regression

4.4.1 Uber

[ ]:
```
pip install xgboost
```

```
Requirement already satisfied: xgboost in /usr/local/lib/python3.10/dist-
packages (2.0.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages
(from xgboost) (1.23.5)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages
(from xgboost) (1.11.4)
```

[ ]:
```
# XGBoost Regression for Uber dataframe
import xgboost as xgb
from xgboost import XGBRegressor
from sklearn.metrics import accuracy_score, mean_squared_error
import numpy as np

xgb_uber = make_pipeline(preprocess_pipeline, XGBRegressor())
xgb_uber.fit(X_train_uber, y_train_uber)
y_pred_uber = xgb_uber.predict(X_test_uber)
xgb_rmses = -cross_val_score(xgb_uber, X_train_uber, y_train_uber,
                              scoring="neg_root_mean_squared_error", cv=3)
print(f"Average XGB Cross-Validation RMSE: {xgb_rmses.mean():.0f}")
```

```
Average XGB Cross-Validation RMSE: 2
```

[ ]:
```
# XGB Grid Search for Uber dataframe
param_grid = {
    'xgbregressor__n_estimators': [50, 100],
    'xgbregressor__max_depth': [3, 5],
    'xgbregressor__colsample_bytree': [0.8, 1.0]
}

xgb_uber_grid_search = GridSearchCV(xgb_uber, param_grid, cv=2,␣
 ↪scoring='neg_root_mean_squared_error', n_jobs=-1)
xgb_uber_grid_search.fit(X_train_uber, y_train_uber)

#Evaluate Performance
y_pred_grid = xgb_uber_grid_search.predict(X_test_uber)
rmse_grid = np.sqrt(mean_squared_error(y_test_uber, y_pred_grid))
print(f"Grid Search RMSE: {rmse_grid}")
```

```
Grid Search RMSE: 1.8760529844851286
```

```
[ ]: # Presenting result
xgb_uber_grid = pd.DataFrame(xgb_uber_grid_search.cv_results_)
xgb_uber_grid.sort_values(by="mean_test_score", ascending=False, inplace=True)
xgb_uber_grid.filter(regex='(^param_|mean_test_score)', axis=1).head(10)
```

```
[ ]:   param_xgbregressor__colsample_bytree param_xgbregressor__max_depth  \
3                                   0.8                             5
7                                   1.0                             5
2                                   0.8                             5
6                                   1.0                             5
5                                   1.0                             3
1                                   0.8                             3
4                                   1.0                             3
0                                   0.8                             3

  param_xgbregressor__n_estimators  mean_test_score
3                              100        -1.889813
7                              100        -1.892140
2                               50        -1.906587
6                               50        -1.906973
5                              100        -1.942402
1                              100        -1.948609
4                               50        -2.026792
0                               50        -2.029297
```

```
[ ]: # XGB Random Search for Uber dataframe
param_grid = {
    'xgbregressor__n_estimators': [50, 100],
    'xgbregressor__max_depth': [3, 5],
    'xgbregressor__colsample_bytree': [0.8, 1.0]
}

xgb_uber_Random_search = RandomizedSearchCV(xgb_uber, param_grid, cv=2,␣
 ↪scoring='neg_root_mean_squared_error', n_jobs=-1)
xgb_uber_Random_search.fit(X_train_uber, y_train_uber)

#Evaluate Performance
y_pred_Random = xgb_uber_Random_search.predict(X_test_uber)
rmse_Random = np.sqrt(mean_squared_error(y_test_uber, y_pred_Random))
print(f"Random Search RMSE: {rmse_Random}")
```

```
Random Search RMSE: 1.8760529844851286
```

```
[ ]: # Presenting result
xgb_uber_Random = pd.DataFrame(xgb_uber_Random_search.cv_results_)
xgb_uber_Random.sort_values(by="mean_test_score", ascending=False, inplace=True)
xgb_uber_Random.filter(regex='(^param_|mean_test_score)', axis=1).head(10)
```

[ ]:
```
   param_xgbregressor__n_estimators param_xgbregressor__max_depth  \
3                               100                             5
7                               100                             5
2                                50                             5
6                                50                             5
5                               100                             3
1                               100                             3
4                                50                             3
0                                50                             3

   param_xgbregressor__colsample_bytree  mean_test_score
3                                   0.8        -1.889813
7                                   1.0        -1.892140
2                                   0.8        -1.906587
6                                   1.0        -1.906973
5                                   1.0        -1.942402
1                                   0.8        -1.948609
4                                   1.0        -2.026792
0                                   0.8        -2.029297
```

[ ]:
```python
# XGB Bayes Search for Uber dataframe
param_bayes = {
    'xgbregressor__n_estimators': (50, 200),
    'xgbregressor__max_depth': (3, 7),
    'xgbregressor__colsample_bytree': (0.8, 1.0)
}

xgb_uber_bayes_search = BayesSearchCV(xgb_uber, search_spaces=param_bayes,␣
↪n_iter=10, cv=2, scoring='neg_root_mean_squared_error', n_jobs=-1)
xgb_uber_bayes_search.fit(X_train_uber, y_train_uber)

# Evaluate Performance - Bayes Search
y_pred_bayes = xgb_uber_bayes_search.predict(X_test_uber)
rmse_bayes = np.sqrt(mean_squared_error(y_test_uber, y_pred_bayes))
print(f"Bayes Search RMSE: {rmse_bayes}")
```

```
Bayes Search RMSE: 1.8650364479779769
```

[ ]:
```python
# Presenting result
xgb_uber_bayes = pd.DataFrame(xgb_uber_bayes_search.cv_results_)
xgb_uber_bayes.sort_values(by="mean_test_score", ascending=False, inplace=True)
xgb_uber_bayes.filter(regex='(^param_|mean_test_score)', axis=1).head(10)
```

[ ]:
```
   param_xgbregressor__colsample_bytree param_xgbregressor__max_depth  \
3                              0.900701                             5
7                              0.892691                             6
9                              0.809514                             6
```

```
5                            0.931857                                    7
4                            0.935327                                    4
0                            0.860193                                    7
6                            0.857183                                    7
1                            0.903436                                    7
8                            0.903383                                    4
2                            0.885276                                    4

  param_xgbregressor__n_estimators  mean_test_score
3                              151        -1.886856
7                              145        -1.887563
9                              106        -1.889392
5                               84        -1.891292
4                              147        -1.895702
0                              125        -1.896715
6                              154        -1.899093
1                              191        -1.902590
8                               90        -1.905684
2                               54        -1.930349
```

4.4.2 Lyft

```
[ ]: # XGBoost Regression for Lyft dataframe
xgb_lyft = make_pipeline(preprocess_pipeline, XGBRegressor())
xgb_lyft.fit(X_train_lyft, y_train_lyft)
y_pred_lyft = xgb_lyft.predict(X_test_lyft)
xgb_rmses = -cross_val_score(xgb_lyft, X_train_lyft, y_train_lyft,
                              scoring="neg_root_mean_squared_error", cv=3)
print(f"Average XGB Cross-Validation RMSE: {xgb_rmses.mean():.0f}")
```

```
Average XGB Cross-Validation RMSE: 3
```

```
[ ]: # XGB Grid Search for lyft dataframe
param_grid = {
    'xgbregressor__n_estimators': [50, 100],
    'xgbregressor__max_depth': [3, 5],
    'xgbregressor__colsample_bytree': [0.8, 1.0]
}

xgb_lyft_grid_search = GridSearchCV(xgb_lyft, param_grid, cv=2,␣
 ↪scoring='neg_root_mean_squared_error', n_jobs=-1)
xgb_lyft_grid_search.fit(X_train_lyft, y_train_lyft)

#Evaluate Performance
y_pred_grid = xgb_lyft_grid_search.predict(X_test_lyft)
rmse_grid = np.sqrt(mean_squared_error(y_test_lyft, y_pred_grid))
print(f"Grid Search RMSE: {rmse_grid}")
```

```
Grid Search RMSE: 2.9914378947719418
```

[ ]:
```python
# Presenting result
xgb_lyft_grid = pd.DataFrame(xgb_lyft_grid_search.cv_results_)
xgb_lyft_grid.sort_values(by="mean_test_score", ascending=False, inplace=True)
xgb_lyft_grid.filter(regex='(^param_|mean_test_score)', axis=1).head(10)
```

[ ]:
```
  param_xgbregressor__colsample_bytree param_xgbregressor__max_depth  \
3                                  0.8                             5
7                                  1.0                             5
6                                  1.0                             5
2                                  0.8                             5
5                                  1.0                             3
1                                  0.8                             3
4                                  1.0                             3
0                                  0.8                             3

  param_xgbregressor__n_estimators  mean_test_score
3                              100        -2.990797
7                              100        -2.991257
6                               50        -3.022386
2                               50        -3.024419
5                              100        -3.052865
1                              100        -3.064362
4                               50        -3.097627
0                               50        -3.113629
```

[ ]:
```python
# XGB Random Search for lyft dataframe
param_grid = {
    'xgbregressor__n_estimators': [50, 100],
    'xgbregressor__max_depth': [3, 5],
    'xgbregressor__subsample': [0.8, 1.0],
}

xgb_lyft_Random_search = RandomizedSearchCV(xgb_lyft, param_grid, cv=2,␣
↪scoring='neg_root_mean_squared_error', n_jobs=-1)
xgb_lyft_Random_search.fit(X_train_lyft, y_train_lyft)

#Evaluate Performance
y_pred_Random = xgb_lyft_Random_search.predict(X_test_lyft)
rmse_Random = np.sqrt(mean_squared_error(y_test_lyft, y_pred_Random))
print(f"Random Search RMSE: {rmse_Random}")
```

```
Random Search RMSE: 2.9910621413885305
```

[ ]:
```python
# Presenting result
xgb_lyft_Random = pd.DataFrame(xgb_lyft_Random_search.cv_results_)
```

```
xgb_lyft_Random.sort_values(by="mean_test_score", ascending=False, inplace=True)
xgb_lyft_Random.filter(regex='(^param_|mean_test_score)', axis=1).head(10)
```

[ ]:
```
  param_xgbregressor__subsample param_xgbregressor__n_estimators  \
7                           1.0                              100
6                           0.8                              100
4                           0.8                               50
5                           1.0                               50
2                           0.8                              100
3                           1.0                              100
0                           0.8                               50
1                           1.0                               50

  param_xgbregressor__max_depth  mean_test_score
7                             5        -2.991257
6                             5        -2.998062
4                             5        -3.019814
5                             5        -3.022386
2                             3        -3.051192
3                             3        -3.052865
0                             3        -3.093635
1                             3        -3.097627
```

[ ]:
```
# XGB Bayes Search for lyft dataframe
param_bayes = {
    'xgbregressor__n_estimators': (50, 200),
    'xgbregressor__max_depth': (3, 7),
    'xgbregressor__subsample': (0.8, 1.0),
}

xgb_lyft_bayes_search = BayesSearchCV(xgb_lyft, search_spaces=param_bayes,␣
 ↪n_iter=10, cv=2, scoring='neg_root_mean_squared_error', n_jobs=-1)
xgb_lyft_bayes_search.fit(X_train_lyft, y_train_lyft)

# Evaluate Performance - Bayes Search
y_pred_bayes = xgb_lyft_bayes_search.predict(X_test_lyft)
rmse_bayes = np.sqrt(mean_squared_error(y_test_lyft, y_pred_bayes))
print(f"Bayes Search RMSE: {rmse_bayes}")
```

```
Bayes Search RMSE: 2.945334385933961
```

[ ]:
```
# Presenting result
xgb_lyft_bayes = pd.DataFrame(xgb_lyft_bayes_search.cv_results_)
xgb_lyft_bayes.sort_values(by="mean_test_score", ascending=False, inplace=True)
xgb_lyft_bayes.filter(regex='(^param_|mean_test_score)', axis=1).head(10)
```

```
[ ]:   param_xgbregressor__max_depth param_xgbregressor__n_estimators  \
    9                              5                              198
    8                              6                               82
    3                              6                               79
    6                              6                               62
    2                              5                              113
    1                              4                              126
    7                              5                               74
    5                              5                               55
    0                              4                               66
    4                              3                              103

      param_xgbregressor__subsample  mean_test_score
    9                      0.946131        -2.964890
    8                      0.977843        -2.980644
    3                      0.986264        -2.982536
    6                      0.891606        -2.986291
    2                      0.880322        -2.987961
    1                      0.810927        -3.006045
    7                      0.878889        -3.006896
    5                       0.86137        -3.012315
    0                      0.823544        -3.034166
    4                      0.933904        -3.053316
```

4.5 Voting Classifier

```
[ ]: from sklearn.ensemble import VotingRegressor
     from sklearn.metrics import mean_squared_error
     import numpy as np


     # Create Uber Voting Classifier
     voting_regressor_uber = VotingRegressor(estimators=[
         ('logreg', lin_reg_uber),
         ('decision_tree', tree_uber),
         ('xgboost', xgb_uber),
         ('elastic_net', elastic_net_uber)
     ])

     # Fit and predict the voting classifier
     voting_regressor_uber.fit(X_train_uber, y_train_uber)
     uber_predictions = voting_regressor_uber.predict(X_test_uber)

     # Calculate RMSE
     rmse = -np.sqrt(mean_squared_error(y_test_uber, uber_predictions))
```

```python
print(f'Voting Regressor RMSE: {rmse}')

# Create Lyft Voting Classifier
voting_regressor_lyft = VotingRegressor(estimators=[
    ('logreg', lin_reg_lyft),
    ('decision_tree', tree_lyft),
    ('xgboost', xgb_lyft),
    ('elastic_net', elastic_net_lyft)
])

# Fit and predict the voting classifier
voting_regressor_lyft.fit(X_train_lyft, y_train_lyft)
lyft_predictions = voting_regressor_lyft.predict(X_test_lyft)

# Calculate RMSE
rmse = -np.sqrt(mean_squared_error(y_test_lyft, lyft_predictions))
print(f'Voting Regressor RMSE: {rmse}')
```

```
Voting Regressor RMSE: -2.6287571923463147
Voting Regressor RMSE: -3.6599796659916417
```

Since voting classifier takes the average RMSE of the four models, we cannot identify the best model. We decided to go forward with hyper-parameter tuning.

5 Feature importance

To determine the best model for price prediction for Uber and Lyft, we will select the model with the maximum Negative Root Mean Squared Error (NRMSE).

[ ]:
```python
import pandas as pd

dataframes_uber = [lin_uber_cv,
              lin_uber_rnd_res,
              lin_uber_bayes_res,
              tree_uber_cv,
              tree_uber_rnd_res,
              tree_uber_bayes_res,
              elastic_net_uber_cv,
              elastic_net_uber_rnd_res,
              elastic_net_uber_bayes_search,
              xgb_uber_grid,
              xgb_uber_Random,
              xgb_uber_bayes]

# Loop through the 12 models and find the maximum mean_test_score
for df in dataframes_uber:
  df.reset_index(drop=True,inplace=True)
```

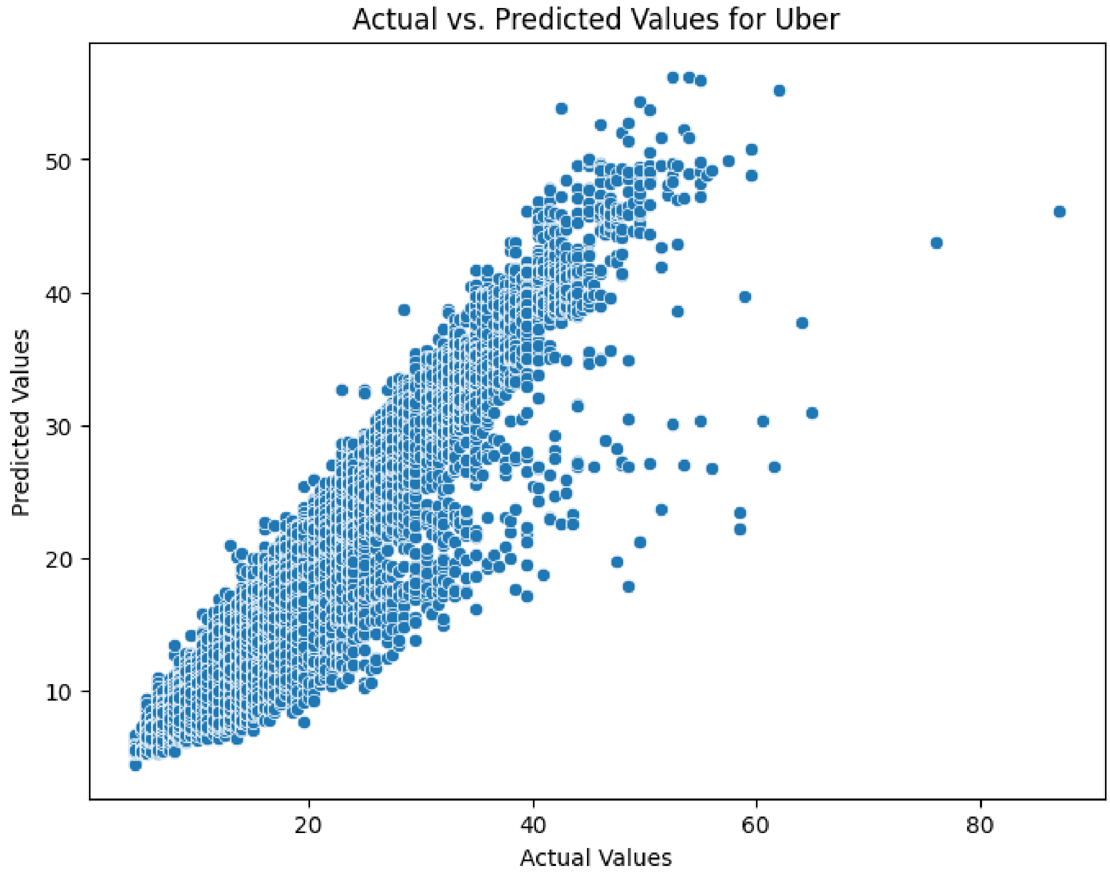
```
subset_values_uber = [df.loc[0,'mean_test_score'] for df in dataframes_uber]

max_value_uber = max(subset_values_uber)
dataframe_name = [name for name, obj in globals().items() if obj is␣
 ↪dataframes_uber[subset_values_uber.index(max_value_uber)]][0]

print("Best Model for Uber prediction is", dataframe_name, ": ", max_value_uber)

dataframes_lyft = [lin_lyft_cv,
              lin_lyft_rnd_res,
              lin_lyft_bayes_res,
              tree_lyft_cv,
              tree_lyft_rnd_res,
              tree_lyft_bayes_res,
              elastic_net_lyft_cv,
              elastic_net_lyft_rnd_res,
              elastic_net_lyft_bayes_search,
              xgb_lyft_grid,
              xgb_lyft_Random,
              xgb_lyft_bayes]
# Identify the best model
for df in dataframes_lyft:
  df.reset_index(drop=True,inplace=True)

subset_values_lyft = [df.loc[0,'mean_test_score'] for df in dataframes_lyft]

max_value_lyft = max(subset_values_lyft)
dataframe_name = [name for name, obj in globals().items() if obj is␣
 ↪dataframes_lyft[subset_values_lyft.index(max_value_lyft)]][0]

print("Best Model for Lyft prediction is", dataframe_name, ": ", max_value_lyft)
```

```
Best Model for Uber prediction is xgb_uber_bayes :  -1.886856033451432
Best Model for Lyft prediction is xgb_lyft_bayes :  -2.9648903786512717
```

[ ]:
```
# Uber actual vs. predicted values
y_pred_bayes_uber = xgb_uber_bayes_search.best_estimator_.predict(X_test_uber)

result_df_uber = pd.DataFrame({'Actual': y_test_uber, 'Predicted':␣
 ↪y_pred_bayes_uber})
result_df_uber = result_df_uber.sort_values(by='Actual')
```

[ ]:
```
# Plot a scatter plot to compare actual vs. predicted values
plt.figure(figsize=(8, 6))
```

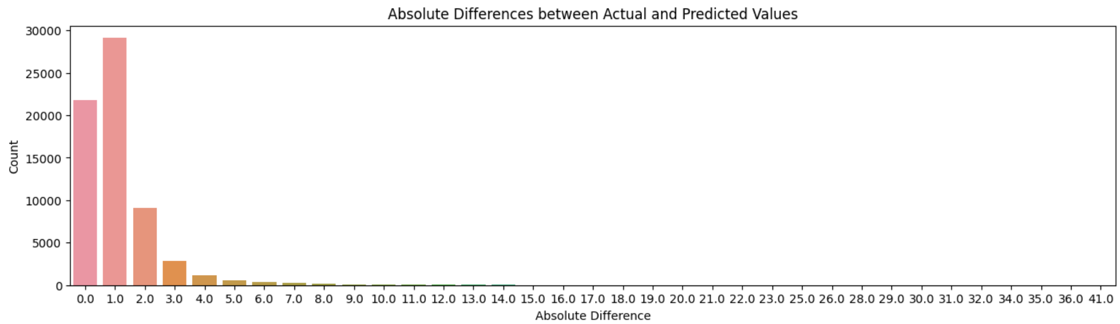
```
sns.scatterplot(x='Actual', y='Predicted', data=result_df_uber,␣
 ↪palette='viridis')
plt.title('Actual vs. Predicted Values for Uber')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.show()
```



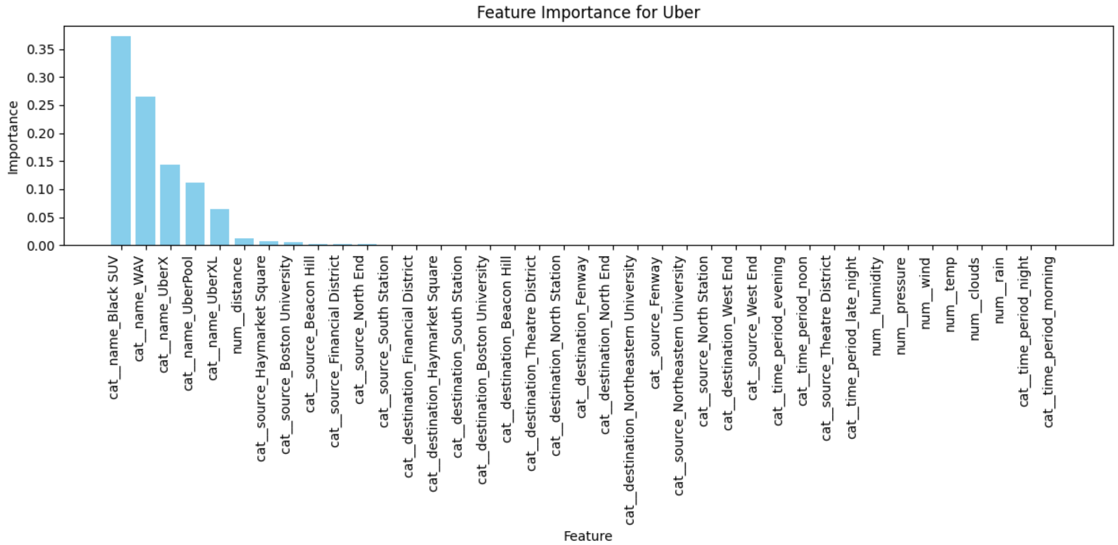
[ ]:
```
import seaborn as sns
import matplotlib.pyplot as plt

result_df_uber['diff'] = abs(result_df_uber['Actual'] -␣
 ↪result_df_uber['Predicted']).round()

sorted_diff_uber = result_df_uber['diff'].sort_values(ascending=True)
```

[ ]:
```
# Create a count plot using seaborn
plt.figure(figsize=(16, 4))
sns.countplot(x = sorted_diff_uber)
plt.title('Absolute Differences between Actual and Predicted Values')
```

```
plt.xlabel('Absolute Difference')
plt.ylabel('Count')
plt.show()
```

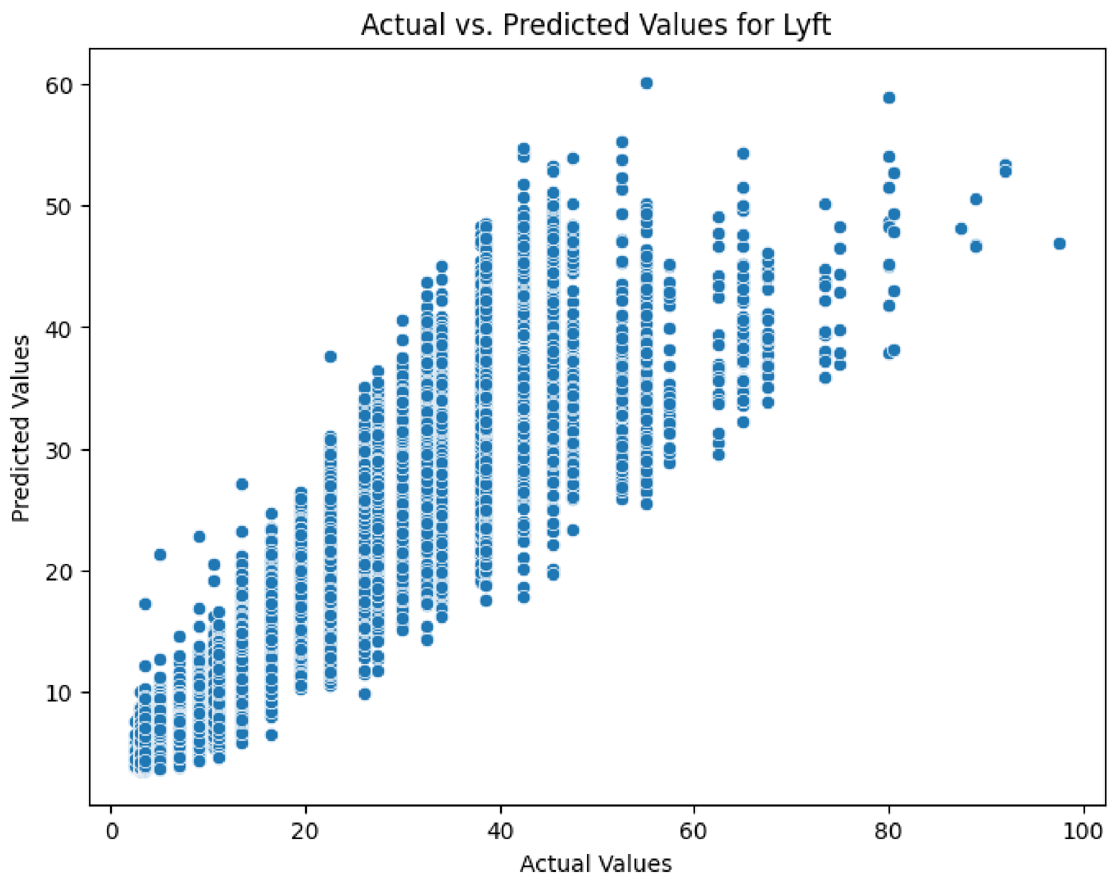



```
[ ]: # plotting importance feature for Uber
feature_importances_uber = xgb_uber_bayes_search.best_estimator_.
 ↪named_steps['xgbregressor'].feature_importances_

feature_names_uber = xgb_uber_bayes_search.best_estimator_[:-1].
 ↪get_feature_names_out()

importance_df_uber = pd.DataFrame({'Feature': feature_names_uber, 'Importance':␣
 ↪feature_importances_uber})

importance_df_uber = importance_df_uber.sort_values(by='Importance',␣
 ↪ascending=False)

plt.figure(figsize=(12, 6))
plt.bar(importance_df_uber['Feature'], importance_df_uber['Importance'],␣
 ↪color='skyblue')
plt.xlabel('Feature')
plt.ylabel('Importance')
plt.title('Feature Importance for Uber')
plt.xticks(rotation=90, ha='right')
plt.tight_layout()
plt.show()
```



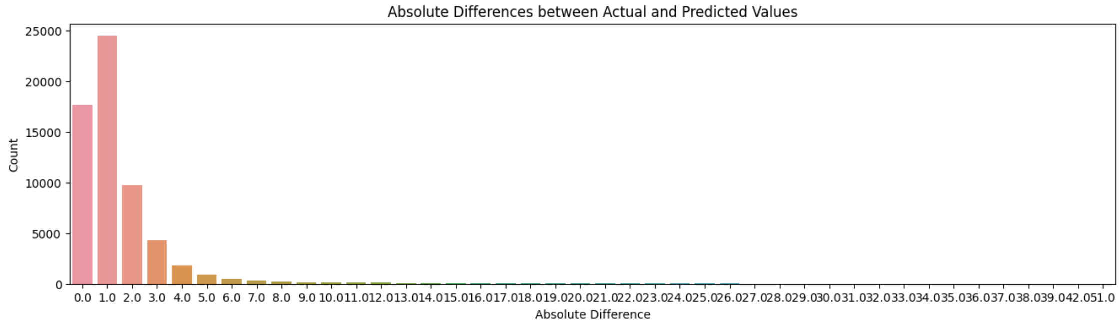
```
[ ]: # Lyft actual vs. predicted values
y_pred_tree_lyft = xgb_lyft_bayes_search.predict(X_test_lyft)
result_df_lyft = pd.DataFrame({'Actual': y_test_lyft, 'Predicted':␣
 ↪y_pred_tree_lyft})
result_df_lyft = result_df_lyft.sort_values(by='Actual')
```

```
[ ]: # plotting compare actual against predicted values
plt.figure(figsize=(8, 6))
sns.scatterplot(x='Actual', y='Predicted', data=result_df_lyft,␣
 ↪palette='viridis')
plt.title('Actual vs. Predicted Values for Lyft')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.show()
```

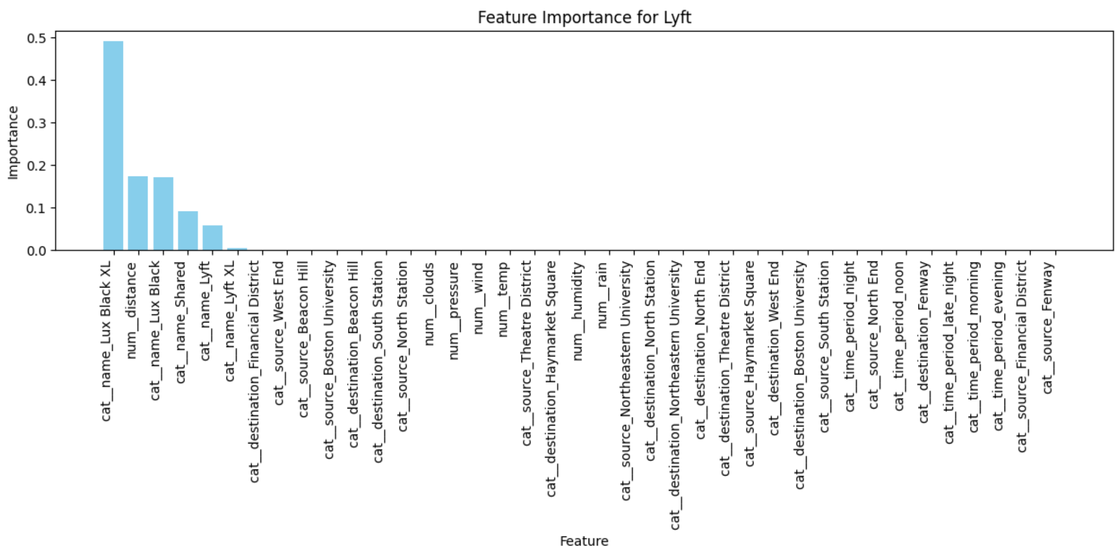


[ ]:
```python
result_df_lyft['diff'] = abs(result_df_lyft['Actual'] -
    result_df_lyft['Predicted']).round()

sorted_diff_lyft = result_df_lyft['diff'].sort_values(ascending=True)
```

[ ]:
```python
# Create a count plot using seaborn
plt.figure(figsize=(16, 4))
sns.countplot(x=sorted_diff_lyft)
plt.title('Absolute Differences between Actual and Predicted Values')
plt.xlabel('Absolute Difference')
plt.ylabel('Count')
plt.show()
```



[ ]:
```
# plotting importance feature for Lyft
feature_importances_lyft = tree_lyft_bayesian_search.best_estimator_.
    ↪named_steps['decisiontreeregressor'].feature_importances_

feature_names_lyft = tree_lyft_bayesian_search.best_estimator_[:-1].
    ↪get_feature_names_out()

importance_df_lyft = pd.DataFrame({'Feature': feature_names_lyft, 'Importance':␣
    ↪feature_importances_lyft})

importance_df_lyft = importance_df_lyft.sort_values(by='Importance',␣
    ↪ascending=False)

plt.figure(figsize=(12, 6))
plt.bar(importance_df_lyft['Feature'], importance_df_lyft['Importance'],␣
    ↪color='skyblue')
plt.xlabel('Feature')
plt.ylabel('Importance')
plt.title('Feature Importance for Lyft')
plt.xticks(rotation=90, ha='right')
plt.tight_layout()
plt.show()
```



6 Price prediction

[ ]:
```
# Price prediction for Uber
test_data_uber = pd.DataFrame({
    'distance': [4.05],
    'destination': 'Financial District',
    'source': 'Boston University',
    'cab_type' : ['Uber'],
    'name': ['UberXL'],
    'temp': [39],
    'clouds': [0.7],
    'pressure': [1008],
    'rain': [0.05],
    'humidity': [0.76],
    'wind': [6.8],
    'time_period': ['afternoon']
})
test_data_uber
```

[ ]:
```
   distance         destination             source cab_type    name  temp  \
0      4.05  Financial District  Boston University     Uber  UberXL    39

   clouds  pressure  rain  humidity  wind time_period
0     0.7      1008  0.05      0.76   6.8   afternoon
```

[ ]:
```
# Price prediction  for Lyft
test_data_lyft = pd.DataFrame({
```

```
    'distance': [4.05],
    'destination': 'Financial District',
    'source': 'Boston University',
    'cab_type' : ['Lyft'],
    'name': ['Lyft XL'],
    'temp': [39],
    'clouds': [0.7],
    'pressure': [1008],
    'rain': [0.05],
    'humidity': [0.76],
    'wind': [6.8],
    'time_period': ['afternoon']
})
test_data_lyft
```

[ ]:
```
   distance         destination             source cab_type     name  temp  \
0      4.05  Financial District  Boston University     Lyft  Lyft XL    39

   clouds  pressure  rain  humidity  wind time_period
0     0.7      1008  0.05      0.76   6.8   afternoon
```

[ ]:
```
data_predictions_uber = xgb_uber_bayes_search.best_estimator_.
 ↪predict(test_data_uber)
print("The prediction price of Uber is", data_predictions_uber)
data_predictions_lyft = xgb_lyft_bayes_search.best_estimator_.
 ↪predict(test_data_lyft)
print("The prediction price of Lyft is", data_predictions_lyft)
```

```
The prediction price of Uber is [23.334993]
The prediction price of Lyft is [22.248138]
```

[ ]:
```
# Change the destination
test_data_uber_1 = test_data_uber.copy()
test_data_lyft_1 = test_data_lyft.copy()
test_data_uber_1['destination'] = 'Theatre District'
test_data_lyft_1['destination'] = 'Theatre District'
test_data_uber_1['distance'] = 2.9
test_data_lyft_1['distance'] = 2.9
data_predictions_uber = xgb_uber_bayes_search.best_estimator_.
 ↪predict(test_data_uber_1)
print("The prediction price of Uber is", data_predictions_uber)
data_predictions_lyft = xgb_lyft_bayes_search.best_estimator_.
 ↪predict(test_data_lyft_1)
print("The prediction price of Lyft is", data_predictions_lyft)
```

```
The prediction price of Uber is [18.100248]
The prediction price of Lyft is [20.249187]
```

[ ]:
```
# Change the time_period
test_data_uber_2 = test_data_uber.copy()
test_data_lyft_2 = test_data_lyft.copy()
test_data_uber_2['time_period'] = 'evening'
test_data_lyft_2['time_period'] = 'evening'
data_predictions_uber = xgb_uber_bayes_search.best_estimator_.
 ↪predict(test_data_uber_2)
print("The prediction price of Uber is", data_predictions_uber)
data_predictions_lyft = xgb_lyft_bayes_search.best_estimator_.
 ↪predict(test_data_lyft_2)
print("The prediction price of Lyft is", data_predictions_lyft)
```

```
The prediction price of Uber is [23.310923]
The prediction price of Lyft is [22.345005]
```

[ ]:
```
# Change the Vehicle type
test_data_uber_2 = test_data_uber.copy()
test_data_lyft_2 = test_data_lyft.copy()
test_data_uber_2['name'] = 'Black SUV'
test_data_lyft_2['name'] = 'Lux Black XL'
data_predictions_uber = xgb_uber_bayes_search.best_estimator_.
 ↪predict(test_data_uber_2)
print("The prediction price of Uber is", data_predictions_uber)
data_predictions_lyft = xgb_lyft_bayes_search.best_estimator_.
 ↪predict(test_data_lyft_2)
print("The prediction price of Lyft is", data_predictions_lyft)

test_data_uber_1
```

```
The prediction price of Uber is [40.76876]
The prediction price of Lyft is [43.09772]
```

[ ]:
```
   distance       destination             source cab_type    name  temp  \
0       2.9  Theatre District  Boston University     Uber  UberXL    39

   clouds  pressure  rain  humidity  wind time_period
0     0.7      1008  0.05      0.76   6.8   afternoon
```

7 Predictions on test data

[ ]:
```
# Uber predictions with best estimator
data_predictions_uber = xgb_uber_bayes_search.best_estimator_.
 ↪predict(X_test_uber)
data_predictions_uber = pd.DataFrame(data_predictions_uber)
X_test_uber = X_test_uber.reset_index()
X_test_uber['predicted_price'] = data_predictions_uber
```

```
X_test_uber.head(10)
```

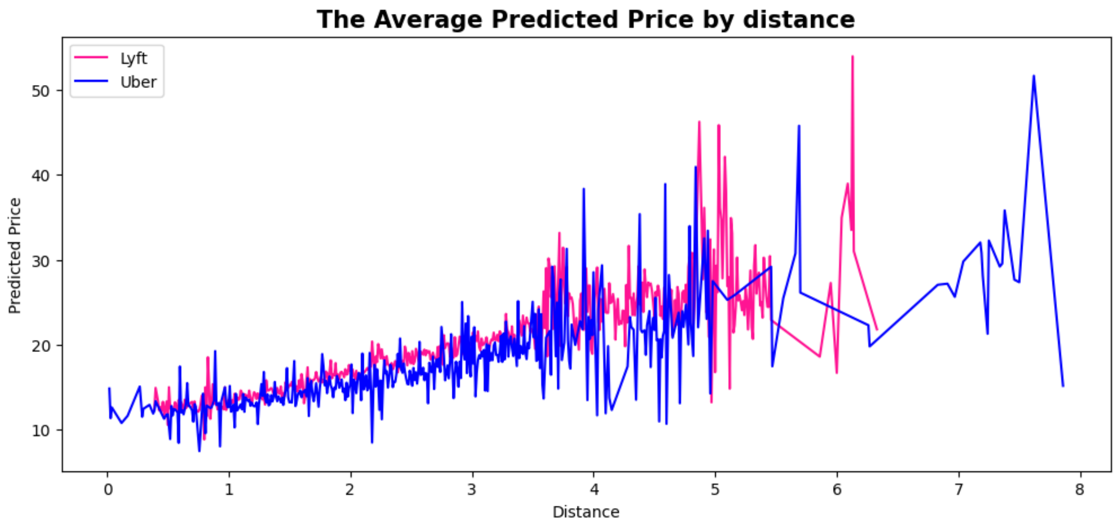
```
[ ]:     index  distance cab_type                destination  \
0  460051      3.01     Uber          Boston University
1  235852      0.56     Uber           Haymarket Square
2  521026      2.72     Uber                   West End
3  369283      1.35     Uber                  North End
4  406967      1.08     Uber  Northeastern University
5  657376      2.65     Uber           Theatre District
6  481690      1.35     Uber           Haymarket Square
7  399507      2.45     Uber              North Station
8  528035      2.34     Uber                   Back Bay
9   51934      1.92     Uber  Northeastern University

                    source       name       temp    clouds     pressure  \
0            North Station        WAV  32.280000  0.690000  1033.670000
1            North Station     UberX  50.740000  1.000000  1003.250000
2                   Fenway     UberX  40.430000  0.890000  1014.006000
3              Beacon Hill    UberXL  41.310000  0.893333   991.560000
4                 Back Bay     Black  41.153333  0.633333   991.586667
5                   Fenway        WAV  48.600000  0.560000  1021.350000
6              Beacon Hill  Black SUV  23.980000  0.500000  1008.790000
7  Northeastern University        WAV  19.940000  0.450000  1031.710000
8                North End   UberPool  42.960000  0.965000   988.545000
9              Beacon Hill  Black SUV  51.840000  0.710000  1021.600000

    rain  humidity       wind time_period  predicted_price
0  0.000  0.560000   2.360000     evening        11.093656
1  0.000  0.930000   3.930000     evening         7.184306
2  0.000  0.932000   2.634000  late_night        10.275254
3  0.002  0.633333   9.490000   afternoon        13.635898
4  0.000  0.623333  10.113333   afternoon        15.626392
5  0.000  0.720000   5.370000     evening        10.958372
6  0.000  0.510000  14.930000        noon        26.742880
7  0.000  0.630000   2.740000        noon        11.089293
8  0.000  0.895000   9.720000   afternoon        10.013367
9  0.000  0.750000   6.740000   afternoon        26.821289
```

```
[ ]: # Lyft predictions with best estimator
data_predictions_lyft = xgb_lyft_bayes_search.best_estimator_.
 ↪predict(X_test_lyft)
data_predictions_lyft = pd.DataFrame(data_predictions_lyft)
X_test_lyft = X_test_lyft.reset_index()
X_test_lyft['predicted_price'] = data_predictions_lyft
X_test_lyft.head(10)
```

```
[ ]:     index  distance cab_type        destination           source  \
0  635446      3.19     Lyft  Boston University    North Station
1   13360      3.16     Lyft             Fenway    North Station
2  368367      2.97     Lyft             Fenway         West End
3  324716      0.74     Lyft   Haymarket Square         West End
4  574640      3.15     Lyft  Boston University    North Station
5  496732      2.86     Lyft  Boston University         West End
6  553575      0.53     Lyft      North Station  Haymarket Square
7  215361      2.39     Lyft      North Station    South Station
8  558301      3.17     Lyft  Boston University  Theatre District
9  122649      3.10     Lyft             Fenway  Theatre District

          name    temp    clouds  pressure    rain  humidity      wind  \
0       Shared  46.920  0.910000  1022.170  0.0000  0.880000  3.990000
1         Lyft  45.060  0.980000  1012.140  0.0000  0.880000  5.160000
2  Lux Black XL  39.210  0.440000  1022.810  0.0000  0.740000  7.190000
3       Shared  37.940  1.000000  1020.070  0.0183  0.860000  1.920000
4       Shared  29.880  0.690000  1034.970  0.0000  0.680000  1.950000
5  Lux Black XL  42.860  0.675000   991.295  0.0000  0.715000  8.565000
6  Lux Black XL  42.595  0.790000   990.810  0.0000  0.725000  9.325000
7  Lux Black XL  33.575  0.138333   991.210  0.0000  0.821667  5.773333
8      Lyft XL  29.820  0.710000  1035.070  0.0000  0.720000  1.610000
9         Lyft  34.100  1.000000  1003.700  0.0100  0.940000  9.320000

  time_period  predicted_price
0   afternoon         6.929302
1     evening        10.729082
2     morning        33.897461
3     morning         4.331971
4       night         6.764403
5     evening        34.063202
6     evening        27.014526
7        noon        32.993515
8  late_night        18.120478
9        noon        12.647260
```

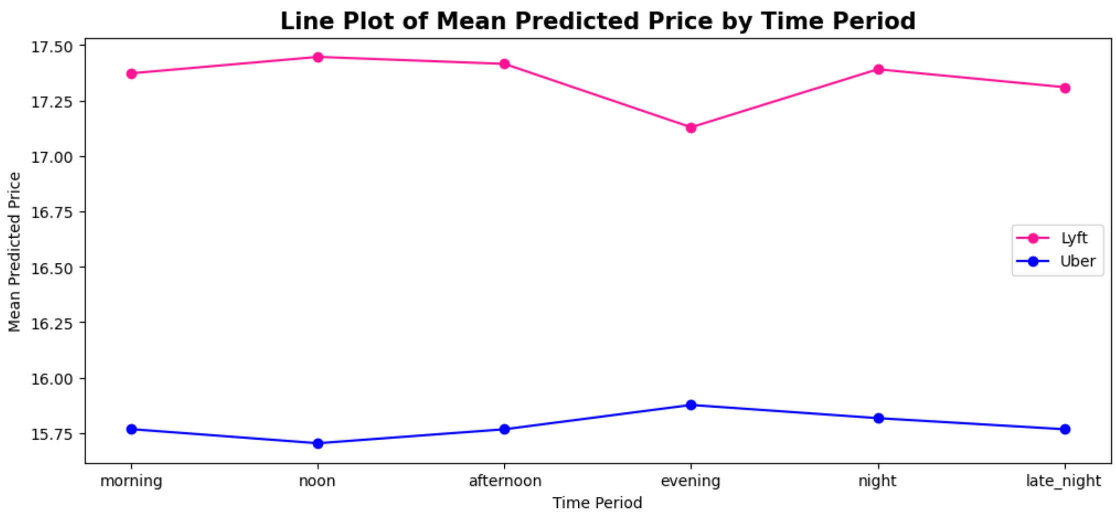
```
[ ]: # plotting distance against predicted price
fig , ax = plt.subplots(figsize = (12,5))
ax.plot(X_test_lyft.groupby('distance').predicted_price.mean().index,␣
 ↪X_test_lyft.groupby('distance').predicted_price.mean(), label = 'Lyft',␣
 ↪color='deeppink')
ax.plot(X_test_uber.groupby('distance').predicted_price.mean().index,␣
 ↪X_test_uber.groupby('distance').predicted_price.mean(), label = 'Uber',␣
 ↪color='blue')
ax.set_title('The Average Predicted Price by distance', fontsize= 15,␣
 ↪fontweight='bold')
ax.set(xlabel = 'Distance', ylabel = 'Predicted Price' )
```

```
ax.legend()
plt.show()
```



Upon comparing the actual price with the average predicted price, we observed that the latter is consistently higher. Furthermore, beyond a distance of five miles, the average predicted price shows greater fluctuation, potentially attributed to a reduced number of data points.

[ ]:
```
# plotting time period against predicted price
time_period_order = ['morning', 'noon', 'afternoon', 'evening', 'night',␣
↪'late_night']
fig, ax = plt.subplots(figsize=(12, 5))

# reorder the dataframe based on time_period_order
lyft_df_ordered = X_test_lyft.groupby('time_period').predicted_price.mean().
↪loc[time_period_order]
uber_df_ordered = X_test_uber.groupby('time_period').predicted_price.mean().
↪loc[time_period_order]

ax.plot(lyft_df_ordered.index, lyft_df_ordered, label='Lyft', color='deeppink',␣
↪linestyle='-', marker='o')
ax.plot(uber_df_ordered.index, uber_df_ordered, label='Uber', color='blue',␣
↪linestyle='-', marker='o')

ax.set_title('Line Plot of Mean Predicted Price by Time Period', fontsize=15,␣
↪fontweight='bold')
ax.set(xlabel='Time Period', ylabel='Mean Predicted Price')
ax.legend()

plt.show()
```



Overall, the average predicted price for Lyft is constantly higher than Uber.

Unexpectedly, we observed a price decrease during the evening period for Lyft, in contrast to a price increase for Uber. We speculate that Lyft reduces prices during this time to enhance competitiveness, particularly during peak demand hours.

8 Challenges

- When joining the trips and weather tables, we found out that the data in the weather table were queried by a 5 minute frequency. The weather table could not direcly be joined on the trips table timestamp, since the date-time might not be exactly the same. To overcome this challenge, we added a new column to take the average weather data by hour, and matched it to the trips table on the hour extracted from the timestamp.
- We had to pick two best models for the Uber and Lyft dataset separately, and since each model had 4 models with 3 search methods, it was challenging to efficiently extract the models with the best performing hyperparameters. To solve this problem, we used for loops to iterate through the different models and the mean test scores. We then used list comprehensions to extract the model with the maximum mean test score and printed out the name of the best-performing models.
- With a large dataset, we had to limit the number of hyperparameters that we tune in order to run the models efficiently.

9 Conclusion

In conclusion, the XGBoost regression model demonstrated the best performance for predicting both Uber and Lyft prices, with the lowest root mean squared error scores compared to other models tested.

By conducting supervised machine learning to predict Uber and Lyft surge prices, we learned the importance of finding the most accurate and cost-effective machine learning model to solve business problems with limited resources. With time and compute power limitations, we needed to use a select number of hyperparameters to tune our models and find the best prediction model for Uber and Lyft separately.

Feature importance analysis found that the distance traveled was the most influential factor affecting price predictions for both Uber and Lyft. This aligns with intuition as trip distance directly impacts the fare amount. Other top predictors were location attributes like pick-up location, destination, and time period.

Comparisons of actual versus predicted price values showed the XGBoost models were relatively accurate, with most predictions closely aligned or slightly under-estimating the actual fares. The predicted prices fell within a $5 difference for a majority of the test cases.

Overall, our analysis and modeling provides an effective framework to predict Uber and Lyft pricing based on a variety of features like trip details, geographic locations, vehicle types and external factors like weather. The XGBoost approach outperformed other regression models, demonstrating feasibility to deliver accurate price estimates to riders using historical Uber and Lyft data trends. With some refinement, the predictive models show promise to be integrated into passenger travel planning and budgeting use cases going forward.