UBER and LYFT Fare Prediction Model

In [ ]:

Objective

The goal is to create fare price prection model for the ride hailing companies Uber and Lyft in the greater Boston area.

All about data

Following Question were answered about Data:

- How much data is present?
- What attributes/features are continuous valued?
- Which attributes are categorical?
- perform EAD and find insights
- implement ridgem lasso, SGD regressor

In [1]:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from numpy import mean
from numpy import absolute
from numpy import sqrt

from sklearn.preprocessing import OneHotEncoder, LabelEncoder
```

```python
from IPython.display import Image
from scipy import stats
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.linear_model import SGDRegressor
from sklearn.linear_model import ElasticNet
from sklearn import preprocessing,svm
from sklearn.model_selection import KFold
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error,r2_score,mean_squared_error
from sklearn.pipeline import Pipeline
```

In [2]:
```python
data = pd.read_csv("/content/drive/MyDrive/Colab Notebooks/AppliedML/rideshare_k
data.head()
```

Out[2]:

	id	timestamp	hour	day	month	datetime	timezone	sou
0	424553bb-7174-41ea-aeb4-fe06d4f4b9d7	1.544953e+09	9	16	12	2018-12-16 09:30:07	America/New_York	Hayma Sq
1	4bd23055-6827-41c6-b23b-3c491f24e74d	1.543284e+09	2	27	11	2018-11-27 02:00:23	America/New_York	Hayma Sq
2	981a3613-77af-4620-a42a-0c0866077d1e	1.543367e+09	1	28	11	2018-11-28 01:00:22	America/New_York	Hayma Sq
3	c2d88af2-d278-4bfd-a8d0-29ca77cc5512	1.543554e+09	4	30	11	2018-11-30 04:53:02	America/New_York	Hayma Sq
4	e0126e1f-8ca9-4f2e-82b3-50505a09db9a	1.543463e+09	3	29	11	2018-11-29 03:49:20	America/New_York	Hayma Sq

5 rows × 57 columns

In [3]:
```python
data.shape
```

Out[3]:
```
(693071, 57)
```

Answer:

1. Data has 693071 rows and 57 columns

In [4]:
```
data.columns
```

Out[4]:
```
Index(['id', 'timestamp', 'hour', 'day', 'month', 'datetime', 'timezone',
       'source', 'destination', 'cab_type', 'product_id', 'name', 'price',
       'distance', 'surge_multiplier', 'latitude', 'longitude', 'temperature',
       'apparentTemperature', 'short_summary', 'long_summary',
       'precipIntensity', 'precipProbability', 'humidity', 'windSpeed',
       'windGust', 'windGustTime', 'visibility', 'temperatureHigh',
       'temperatureHighTime', 'temperatureLow', 'temperatureLowTime',
       'apparentTemperatureHigh', 'apparentTemperatureHighTime',
       'apparentTemperatureLow', 'apparentTemperatureLowTime', 'icon',
       'dewPoint', 'pressure', 'windBearing', 'cloudCover', 'uvIndex',
       'visibility.1', 'ozone', 'sunriseTime', 'sunsetTime', 'moonPhase',
       'precipIntensityMax', 'uvIndexTime', 'temperatureMin',
       'temperatureMinTime', 'temperatureMax', 'temperatureMaxTime',
       'apparentTemperatureMin', 'apparentTemperatureMinTime',
       'apparentTemperatureMax', 'apparentTemperatureMaxTime'],
      dtype='object')
```

In [5]:
```
data.nunique(axis=0)
```

```
Out[5]: id                             693071
        timestamp                       36179
        hour                               24
        day                                17
        month                               2
        datetime                        31350
        timezone                            1
        source                             12
        destination                        12
        cab_type                            2
        product_id                         13
        name                               13
        price                             147
        distance                          549
        surge_multiplier                    7
        latitude                           11
        longitude                          12
        temperature                       308
        apparentTemperature               319
        short_summary                       9
        long_summary                       11
        precipIntensity                    63
        precipProbability                  29
        humidity                           51
        windSpeed                         291
        windGust                          286
        windGustTime                       25
        visibility                        227
        temperatureHigh                   129
        temperatureHighTime                23
        temperatureLow                    133
        temperatureLowTime                 31
        apparentTemperatureHigh           124
        apparentTemperatureHighTime        27
        apparentTemperatureLow            136
        apparentTemperatureLowTime         32
        icon                                7
        dewPoint                          313
        pressure                          316
        windBearing                       195
        cloudCover                         83
        uvIndex                             3
        visibility.1                      227
        ozone                             274
        sunriseTime                       110
        sunsetTime                        114
        moonPhase                          18
        precipIntensityMax                 65
        uvIndexTime                        20
        temperatureMin                    131
        temperatureMinTime                 25
        temperatureMax                    128
        temperatureMaxTime                 23
        apparentTemperatureMin            137
        apparentTemperatureMinTime         29
        apparentTemperatureMax            125
        apparentTemperatureMaxTime         27
        dtype: int64
```

Statstical values for the every column as follows:

In [6]:
```
data.describe().apply(lambda s: s.apply(lambda x: format(x, 'f')))
```

Out[6]:

	timestamp	hour	day	month	price
count	693071.000000	693071.000000	693071.000000	693071.000000	637976.000000
mean	1544045709.755097	11.619137	17.794365	11.586684	16.545125
std	689192.492586	6.948114	9.982286	0.492429	9.324359
min	1543203646.000000	0.000000	1.000000	11.000000	2.500000
25%	1543443968.000000	6.000000	13.000000	11.000000	9.000000
50%	1543737478.000000	12.000000	17.000000	12.000000	13.500000
75%	1544827509.000000	18.000000	28.000000	12.000000	22.500000
max	1545160511.000000	23.000000	30.000000	12.000000	97.500000

8 rows × 46 columns

In [7]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 693071 entries, 0 to 693070
Data columns (total 57 columns):
 #   Column                       Non-Null Count   Dtype  
---  ------                       --------------   -----  
 0   id                           693071 non-null  object 
 1   timestamp                    693071 non-null  float64
 2   hour                         693071 non-null  int64  
 3   day                          693071 non-null  int64  
 4   month                        693071 non-null  int64  
 5   datetime                     693071 non-null  object 
 6   timezone                     693071 non-null  object 
 7   source                       693071 non-null  object 
 8   destination                  693071 non-null  object 
 9   cab_type                     693071 non-null  object 
 10  product_id                   693071 non-null  object 
 11  name                         693071 non-null  object 
 12  price                        637976 non-null  float64
 13  distance                     693071 non-null  float64
 14  surge_multiplier             693071 non-null  float64
 15  latitude                     693071 non-null  float64
 16  longitude                    693071 non-null  float64
 17  temperature                  693071 non-null  float64
 18  apparentTemperature          693071 non-null  float64
 19  short_summary                693071 non-null  object 
 20  long_summary                 693071 non-null  object 
 21  precipIntensity              693071 non-null  float64
 22  precipProbability            693071 non-null  float64
 23  humidity                     693071 non-null  float64
 24  windSpeed                    693071 non-null  float64
 25  windGust                     693071 non-null  float64
 26  windGustTime                 693071 non-null  int64  
 27  visibility                   693071 non-null  float64
 28  temperatureHigh              693071 non-null  float64
 29  temperatureHighTime          693071 non-null  int64  
 30  temperatureLow               693071 non-null  float64
 31  temperatureLowTime           693071 non-null  int64  
 32  apparentTemperatureHigh      693071 non-null  float64
 33  apparentTemperatureHighTime  693071 non-null  int64  
 34  apparentTemperatureLow       693071 non-null  float64
 35  apparentTemperatureLowTime   693071 non-null  int64  
 36  icon                         693071 non-null  object 
 37  dewPoint                     693071 non-null  float64
 38  pressure                     693071 non-null  float64
 39  windBearing                  693071 non-null  int64  
 40  cloudCover                   693071 non-null  float64
 41  uvIndex                      693071 non-null  int64  
 42  visibility.1                 693071 non-null  float64
 43  ozone                        693071 non-null  float64
 44  sunriseTime                  693071 non-null  int64  
 45  sunsetTime                   693071 non-null  int64  
 46  moonPhase                    693071 non-null  float64
 47  precipIntensityMax           693071 non-null  float64
 48  uvIndexTime                  693071 non-null  int64  
 49  temperatureMin               693071 non-null  float64
 50  temperatureMinTime           693071 non-null  int64  
 51  temperatureMax               693071 non-null  float64
 52  temperatureMaxTime           693071 non-null  int64  
 53  apparentTemperatureMin       693071 non-null  float64
 54  apparentTemperatureMinTime   693071 non-null  int64  
```

```
 55  apparentTemperatureMax       693071 non-null  float64
 56  apparentTemperatureMaxTime   693071 non-null  int64
dtypes: float64(29), int64(17), object(11)
memory usage: 301.4+ MB
```

Only Price column has some missing rows.

In [8]:
```
total = data.isnull().sum().sort_values(ascending=False)
percent = (data.isnull().sum()/data.isnull().count()).sort_values(ascending=Fals
missing_data = pd.concat([total,percent],axis=1,keys=["total","percent"])
missing_data.head()
```

Out[8]:

	total	percent
price	55095	0.079494
id	0	0.000000
ozone	0	0.000000
temperatureLowTime	0	0.000000
apparentTemperatureHigh	0	0.000000

8% data in price column is missing

Let's check how many categorical and numerical columns are present in the data.

In [9]:
```
len(data._get_numeric_data().columns)
```

Out[9]: 46

Answer: We have total 46 columns as numeric data columns. Remaining 11 are categorical columns.

In [10]:
```
categorical_cols=data.columns[data.dtypes =='object']
print(categorical_cols)
```

```
Index(['id', 'datetime', 'timezone', 'source', 'destination', 'cab_type',
       'product_id', 'name', 'short_summary', 'long_summary', 'icon'],
      dtype='object')
```

In [ ]:

In [ ]:

Data Cleaning and Transformation

We are removing the following columns:

- Id: This column is solely for unique records.
- Datetime, Timestamp: These are redundant since we already have separate columns for month, day, and hour.
- Timezone: There's only one timezone in the dataset, so it's unnecessary.

- Product_id: We will use the product name instead of the product ID.
- Weather-related columns: We are not considering weather data at the moment, so all weather-related columns will be removed.
- Longitude and Latitude: These are redundant as we already have the destination name.

In [11]:
```
data = data.drop(['id', 'datetime', 'timezone', 'timestamp','latitude', 'longitu
        'apparentTemperature', 'short_summary', 'long_summary',"product_id",
        'precipIntensity', 'precipProbability', 'humidity', 'windSpeed',
        'windGust', 'windGustTime', 'visibility', 'temperatureHigh',
        'temperatureHighTime', 'temperatureLow', 'temperatureLowTime',
        'apparentTemperatureHigh', 'apparentTemperatureHighTime',
        'apparentTemperatureLow', 'apparentTemperatureLowTime', 'icon',
        'dewPoint', 'pressure', 'windBearing', 'cloudCover', 'uvIndex',
        'visibility.1', 'ozone', 'sunriseTime', 'sunsetTime', 'moonPhase',
        'precipIntensityMax', 'uvIndexTime', 'temperatureMin',
        'temperatureMinTime', 'temperatureMax', 'temperatureMaxTime',
        'apparentTemperatureMin', 'apparentTemperatureMinTime',
        'apparentTemperatureMax', 'apparentTemperatureMaxTime'], axis=1)
```

Imputing the mean value in place of missing values.

In [12]:
```
for j in ["price"]:
    data.loc[data.loc[:,j].isnull(),j] = data.loc[:,j].mean()
data.price.isnull().sum()
```

Out[12]:
```
0
```

Exploratory Data Analysis

Let's do some data Exploration via Graph.

We will plot the pairplots for all the columns in the data. Since the pairplot takes forever to run on the entire dataset. we will only take 2000 samples to plot it. Pairplot includes all the scatter plots and histogram of the columns.

In [13]:
```
sns_pairplot=sns.pairplot(data.sample(2000), hue="cab_type", markers=["o","s"],d
```

Diagonal graphs represent the histogram for every column in the modified dataset.

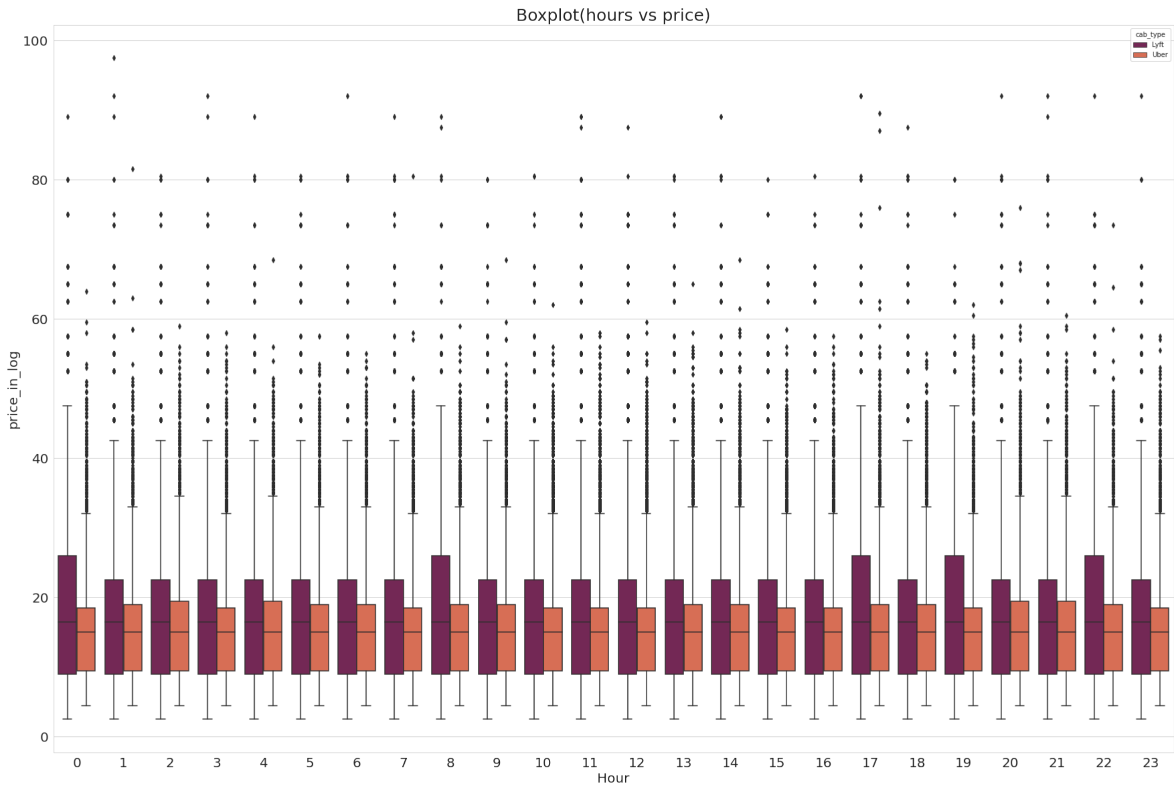
Observation:

Histograms: The histograms of the price, distance, and surge_multiplier columns appear to be skewed. To normalize these distributions, we will need to apply some transformations.

Scatter Plot: The scatter plots indicate a correlation between distance and price, as well as price and surge_multiplier. We will plot a correlation matrix to determine the exact relationships between these attributes and the labels.

Let's plot the boxplots for checking whether there are outliers in the data or not

In [14]:
```
plt.figure(figsize=(30,20))
sns.set_style("whitegrid")
sns.boxplot(x="hour", y="price",data=data, hue="cab_type",palette="rocket")
plt.xticks(fontsize= 20)
plt.yticks(fontsize= 20)
plt.xlabel("Hour",fontsize=20)
plt.ylabel("price_in_log",fontsize=20)
plt.title("Boxplot(hours vs price)",fontsize=25)
plt.show()
```



Observation:

- The price range for Lyft is consistently higher than for Uber.
- There are numerous outliers in the data, particularly in the Uber dataset.

Let's work on removing the outliers:

In [15]:
```
quantiles = stats.mstats.mquantiles(data["price"] , prob=[0.25,0.75])
IQR= stats.iqr(data["price"])
upper = quantiles[1]+(1.5*IQR)
lower = quantiles[0]-(1.5*IQR)
data.loc[data["price"]>upper,"price"]= np.nan
data.loc[data["price"]<lower,"price"]= np.nan
data.price.isnull().sum()
```

Out[15]: 7982

We can see the 7982 outliers are present in the dataset. We can remove them by imputing mean values.

In [16]:
```
for i in ["price"]:
    data.loc[data.loc[:,i].isnull(),i] = data.loc[:,i].mean()
data.price.isnull().sum()
```

Out[16]: 0

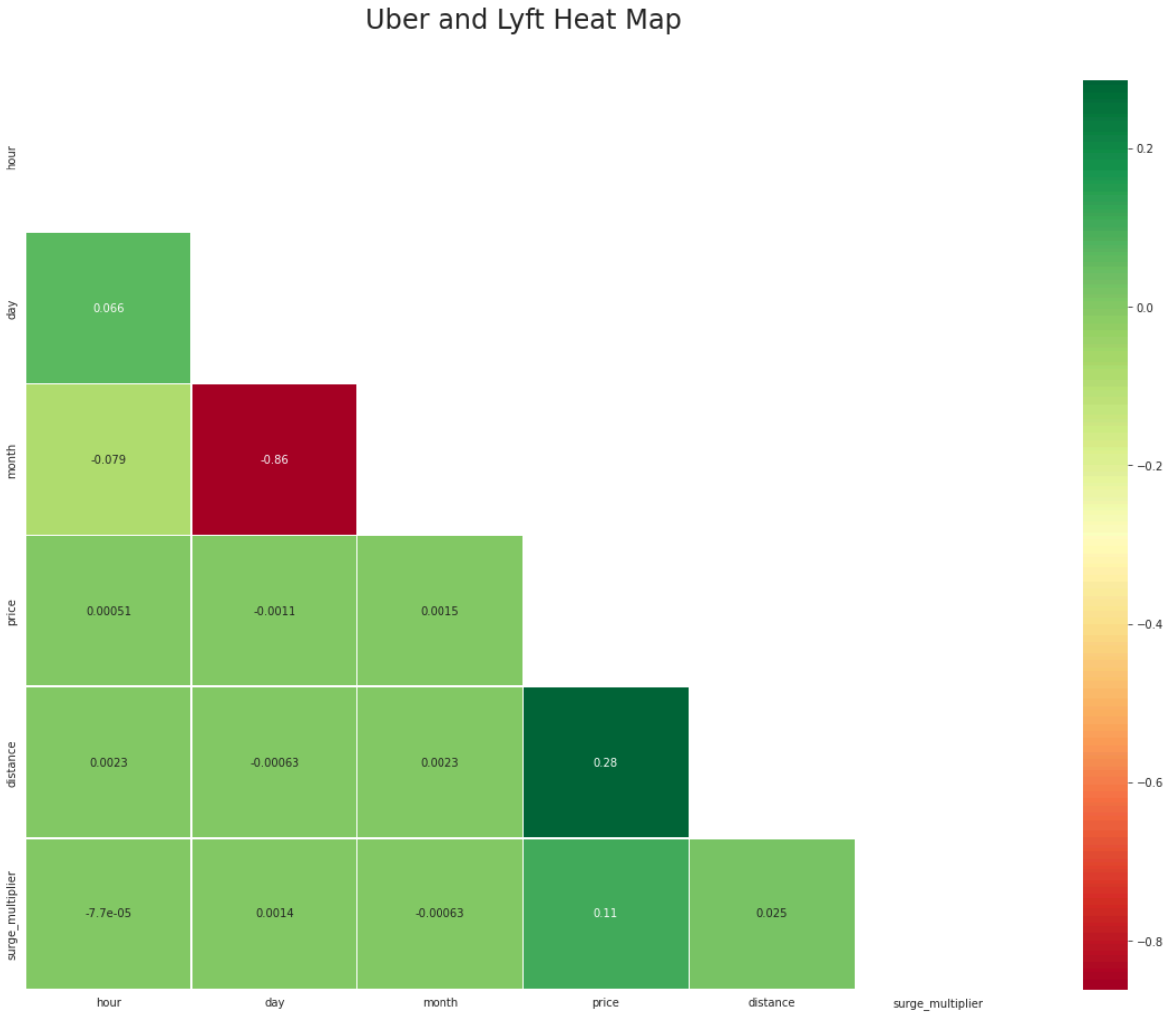
Plotting the PCC for observing the relationaship between columns.

In [17]:
```
corrmat = data.corr()

fig, ax = plt.subplots(figsize=(20,15))
title = "Uber and Lyft Heat Map"
plt.title(title,fontsize=24)
```

```
ttl = ax.title
ttl.set_position([0.5,1.05])
mask = np.triu(np.ones_like(corrmat, dtype=bool))
sns.heatmap(corrmat,mask=mask,annot=True,cmap='RdYlGn',linewidths=0.20,ax=ax)
```

Out[17]: `<matplotlib.axes._subplots.AxesSubplot at 0x7f0eda63f8e0>`



- Price and surge multiplier highly correlated
- Price and distance is correlated
- Distance and surge-multiplier is not correlated

Data Preparation

Extracting categorical columns and numerical columns from the updated dataset:

In [18]:
```
categorical_cols=data.columns[data.dtypes =='object']
print(categorical_cols)
len(categorical_cols)
```

```
Index(['source', 'destination', 'cab_type', 'name'], dtype='object')
```

Out[18]: 4

Let's count the unique values in categorical columns

In [19]:
```python
for i in categorical_cols:
  print(data[i].value_counts())
```

```
Financial District         58857
Theatre District           57813
Back Bay                   57792
Boston University          57764
North End                  57763
Fenway                     57757
Northeastern University    57756
South Station              57750
Haymarket Square           57736
West End                   57562
Beacon Hill                57403
North Station              57118
Name: source, dtype: int64
Financial District         58851
Theatre District           57798
Back Bay                   57780
Haymarket Square           57764
Boston University          57764
Fenway                     57757
North End                  57756
Northeastern University    57755
South Station              57749
West End                   57575
Beacon Hill                57403
North Station              57119
Name: destination, dtype: int64
Uber    385663
Lyft    307408
Name: cab_type, dtype: int64
UberXL          55096
WAV             55096
Black SUV       55096
Black           55095
Taxi            55095
UberX           55094
UberPool        55091
Lux             51235
Lyft            51235
Lux Black XL    51235
Lyft XL         51235
Lux Black       51235
Shared          51233
Name: name, dtype: int64
```

In [20]:
```python
numeric_cols=data._get_numeric_data().columns
print(numeric_cols)
```

```
Index(['hour', 'day', 'month', 'price', 'distance', 'surge_multiplier'], dtype='o
bject')
```

We need to convert categorical columns into numerical columns by one hot encoding and we will perform statndrad scaling on numeric data.

In [21]:
```python
ohe=OneHotEncoder()
data_encode_col = pd.DataFrame(ohe.fit_transform(data[categorical_cols]).toarray
data_encode_col.head()
```

```
data_other_cols = data.drop(columns=categorical_cols)
data = pd.concat([data_encode_col, data_other_cols], axis=1)
```

```
/usr/local/lib/python3.8/dist-packages/sklearn/utils/deprecation.py:87: FutureWarning: Function get_feature_names is deprecated; get_feature_names is deprecated in 1.0 and will be removed in 1.2. Please use get_feature_names_out instead.
  warnings.warn(msg, category=FutureWarning)
```

In [22]:
```
data.head()
```

Out[22]:

	encoded_source_Back Bay	encoded_source_Beacon Hill	encoded_source_Boston University	encoded_sour
0	0.0	0.0	0.0	
1	0.0	0.0	0.0	
2	0.0	0.0	0.0	
3	0.0	0.0	0.0	
4	0.0	0.0	0.0	

5 rows × 45 columns

In [23]:
```
scaler= StandardScaler()
data = pd.DataFrame(scaler.fit_transform(data),columns=data.columns)
```

In [24]:
```
data.head()
```

Out[24]:

	encoded_source_Back Bay	encoded_source_Beacon Hill	encoded_source_Boston University	encoded_sour
0	-0.301614	-0.300505	-0.301534	
1	-0.301614	-0.300505	-0.301534	
2	-0.301614	-0.300505	-0.301534	
3	-0.301614	-0.300505	-0.301534	
4	-0.301614	-0.300505	-0.301534	

5 rows × 45 columns

In [25]:
```
data.shape
```

Out[25]:
```
(693071, 45)
```

Model Training

In [26]:
```
data.dropna(inplace = True)
X=data.drop(['price'],axis=1)
y=data['price']
```

```python
instances = X.shape[0]
features = X.shape[1]

# Converting each dataframe into a numpy array since each dataframe contains onl
X = np.array(X).reshape(-1, features)
y = np.array(y).reshape(-1, 1)

identity_vector = np.asarray([[1 for num in range(instances)]])
identity_vector = identity_vector.reshape(-1,1)
X_train, X_test, y_train, y_test = train_test_split(X,y,train_size=0.8,test_size
# print(X_train, X_test, y_train)
print("Training set shape:", X_train.shape, y_train.shape)
print("Testing set shape:", X_test.shape, y_test.shape)
print("Training set mean:", X_train.mean(), y_train.mean())
print("Testing set mean:", X_test.mean(), y_test.mean())
print("Training set standard deviation:", X_train.std(), y_train.std())
print("Testing set standard deviation:", X_test.std(), y_test.std())
```

```
Training set shape: (554456, 44) (554456, 1)
Testing set shape: (138615, 44) (138615, 1)
Training set mean: -2.124310478650521e-05 -0.00032480055681517354
Testing set mean: 8.497180613571272e-05 0.0012991928545252468
Training set standard deviation: 0.9999617016235108 0.9990762967096172
Testing set standard deviation: 1.0001531732236146 1.0036852346455714
```

Helper function required for model training and evalution:

In [44]:
```python
def evaluate_model(test,pred):
    #print(test,pred)
    print("R^2:", r2_score(test, pred))
    print("MAE:", mean_absolute_error(test,pred))
    print("RMSE:",np.sqrt(mean_squared_error(test, pred)))
    print("")

def create_mini_batches(X, y, batch_size):
    mini_batches = []
    data = np.hstack((X, y))
    np.random.shuffle(data)
    n_minibatches = data.shape[0] // batch_size
    i = 0

    for i in range(n_minibatches + 1):
        mini_batch = data[i * batch_size:(i + 1)*batch_size, :]
        X_mini = mini_batch[:, :-1]
        Y_mini = mini_batch[:, -1].reshape((-1, 1))
        mini_batches.append((X_mini, Y_mini))
    if data.shape[0] % batch_size != 0:
        mini_batch = data[i * batch_size:data.shape[0]]
        X_mini = mini_batch[:, :-1]
        Y_mini = mini_batch[:, -1].reshape((-1, 1))
        mini_batches.append((X_mini, Y_mini))
    return mini_batches

def perform_lr(X_train,X_test,train_y, test_y):
    #X_train = np.append(X_train,identity_vector[:X_train.shape[0],:],1)
    #X_test = np.append(X_test,identity_vector[:X_test.shape[0],:],1)
    lr = LinearRegression()
    lr.fit(X_train,train_y)
    y_val_pred = lr.predict(X_test)
```

```
    y_train_pred = lr.predict(X_train)

    print('Shape:',X_train.shape)
    print('Rank:',np.linalg.matrix_rank(X_train))
    print('coeff:',lr.coef_)
    #Test linear regression model
    print("Training Loss")
    evaluate_model(train_y,y_train_pred)
    print("Validation Loss")
    evaluate_model(test_y,y_val_pred)


def perform_sgd(X_train,train_y, X_test, test_y,alpha=0.0001, epsilon=0.1, eta0=
    print("penalty term:",penalty,",learning rate:",learning_rate,",batch size:"
#     print(train_y)
    X_train = np.append(X_train,identity_vector[:X_train.shape[0],:],1)
    X_test = np.append(X_test,identity_vector[:X_test.shape[0],:],1)
#     print(X_train.shape)
#     print('Rank:',np.linalg.matrix_rank(X_train))
    model = SGDRegressor(alpha=alpha, epsilon=epsilon, eta0=eta0,penalty=penalty
    if batchsize > 1:
        batcherator = create_mini_batches(X_train, train_y,batch_size=batchsize)
        for X_chunk, y_chunk in batcherator:
            y_chunk = y_chunk.squeeze(1)
            model.partial_fit(X_chunk, y_chunk)
    else:
        train_y = train_y.squeeze(1)
        model.fit(X_train, train_y)

    y_val_predicted = model.predict(X_test)
    print("validation loss")
    evaluate_model(test_y,y_val_predicted)

    y_train_predicted = model.predict(X_train)
    print("training loss")
    evaluate_model(train_y,y_train_predicted)



def perform_pr(X_train,X_test,train_y,test_y):
    p = preprocessing.PolynomialFeatures(degree=2)
    X_train_poly = p.fit_transform(X_train)
    X_test_poly = p.fit_transform(X_test)
    X_train_poly = np.append(X_train,identity_vector[:X_train.shape[0],:],1)
    X_test_poly = np.append(X_test,identity_vector[:X_test.shape[0],:],1)
    pr = LinearRegression()
    pr.fit(X_train_poly,train_y)
    y_val_pred = pr.predict(X_test_poly)
    #Test plynomial regression model
    print("validation loss")
    evaluate_model(test_y,y_val_pred)



def add_poly(X_train,X_test):
    p = preprocessing.PolynomialFeatures(degree=2)
    X_train_poly = p.fit_transform(X_train[:,:7])
    X_test_poly = p.fit_transform(X_test[:,:7])
    X_train_poly = StandardScaler().fit_transform(X_train_poly)
    X_test_poly = StandardScaler().fit_transform(X_test_poly)
```

```
#     print(X_train_poly.shape,X_train[:,8:].shape)
    X_train_poly = np.append(X_train_poly,X_train[:,8:],1)
    X_test_poly = np.append(X_test_poly,X_test[:,8:],1)
    return X_train_poly,X_test_poly

def perform_ridge(X_train,train_y,X_test,test_y,alpha=0.5):
    rdg = Ridge(alpha = alpha)
    print("alpha:",alpha)
    rdg.fit(X_train, train_y)
    pred_test_rr= rdg.predict(X_test)
    print("Validation loss")
    evaluate_model(test_y,pred_test_rr)
    y_train_predicted = rdg.predict(X_train)
    print("training loss")
    evaluate_model(train_y,y_train_predicted)


def perform_l(X_train,y_train,X_test,test_y,alpha=0.1):
    model_lasso = Lasso(alpha=alpha)
    model_lasso.fit(X_train, y_train)
    pred_train_lasso= model_lasso.predict(X_test)
    print("alpha:",alpha)
    print("validation loss")
    evaluate_model(test_y,pred_train_lasso)
    y_train_predicted = model_lasso.predict(X_train)
    print("training loss")
    evaluate_model(y_train,y_train_predicted)



def perform_en(X_train, y_train,X_test,test_y,alpha=0.1,l1=0.5):
    model = ElasticNet(alpha=alpha,l1_ratio=l1)
    model.fit(X_train, y_train)
    pred_test = model.predict(X_test)
    print("alpha:",alpha,",l1 ratio:",l1)
    print("validation loss")
    evaluate_model(test_y,pred_test)
    pred_train = model.predict(X_train)

    print("alpha:",alpha,",l1 ratio:",l1)
    print("training loss")
    evaluate_model(y_train,pred_train)





def k_fold_closed(X_train,y_train):
    model = Ridge(alpha=0.000000000000000000000000000000001)
#     model = LinearRegression()
    pipeline = Pipeline([('transformer', StandardScaler()), ('estimator', model)
#     pipeline = Pipeline([('transformer', StandardScaler()), ('model', Transfor


    cv = KFold(n_splits=4, random_state=20, shuffle=True)

    print('Rank:',np.linalg.matrix_rank(X_train))
#     X_train = np.append(X_train,identity_vector[:X_train.shape[0],:],1)
    print('Rank:',np.linalg.matrix_rank(X_train))
    print('Shape:',X_train.shape)
#     X_train = StandardScaler().fit_transform(X_train)
```

```
    scores = cross_val_score(model, X_train, y_train, scoring='neg_mean_absolute
                             cv=cv, n_jobs=-1)
    print(X_train)
    print(scores)
    #view RMSE
    return sqrt(mean(absolute(scores)))

def k_fold_sgd(X_train,train_y):
    cv = KFold(n_splits=4, random_state=1, shuffle=True)
    model = SGDRegressor()
    sgd_x = StandardScaler().fit_transform(X_train)
    sgd_y = train_y.squeeze(1)
    sgd_x = np.append(sgd_x,identity_vector[:sgd_x.shape[0],:],1)
    scores = cross_val_score(model, sgd_x, sgd_y, scoring='neg_mean_absolute_err
                             cv=cv, n_jobs=-1)
    print(scores)
    #view RMSE
    return sqrt(mean(absolute(scores)))
```

In [28]:

```
#Train model using linear regression(closed form)
perform_lr(X_train,X_test,y_train, y_test)
```

```
Shape: (554456, 44)
Rank: 38
coeff: [[-5.84037534e+11 -5.82246808e+11 -2.97862401e+11 -2.97845993e+11
  -5.88900089e+11 -2.97796763e+11 -2.97860057e+11 -5.80929797e+11
  -2.97843649e+11 -2.97829585e+11 -5.84133981e+11 -5.82979706e+11
  -3.69737656e+11 -3.68638791e+11 -8.36446139e+10 -8.36400063e+10
  -3.72833951e+11 -8.36446139e+10 -8.36393481e+10 -3.67807880e+11
  -8.36386898e+10 -8.36347402e+10 -3.69790004e+11 -3.69140713e+11
   6.46350864e+12 -2.00395627e+12  1.81939588e+12  1.81941096e+12
  -2.69970683e+12 -2.69970683e+12 -2.69970683e+12 -2.69970683e+12
  -2.69970683e+12 -2.69965834e+12  1.81939588e+12  1.81933553e+12
   1.81938079e+12  1.81941096e+12  1.81941096e+12  5.38825989e-05
  -2.54249573e-03 -5.00798225e-04  2.90130615e-01  5.83801270e-02]]
Training Loss
R^2: 0.8617481653387474
MAE: 0.2333115486651984
RMSE: 0.3714788624839923

Validation Loss
R^2: 0.8618734465803293
MAE: 0.23472431802629343
RMSE: 0.3730234400548633
```

Observation (Linear regression closed form): There is not much difference between training and validation loss. This indicates that model is performing reasonably well. It's not underfitting or overfitting with dataset.

In [29]:

```
perform_sgd(X_train,y_train, X_test, y_test,penalty='elasticnet',learning_rate='
perform_sgd(X_train,y_train, X_test, y_test,penalty='l1',learning_rate='optimal'
perform_sgd(X_train,y_train, X_test, y_test,penalty='l2',learning_rate='adaptive
perform_sgd(X_train,y_train, X_test, y_test,penalty='l2',learning_rate='invscali
perform_sgd(X_train,y_train, X_test, y_test)
```

```
penalty term: elasticnet ,learning rate: constant ,batch size: 5
validation loss
R^2: 0.8199889146193468
MAE: 0.2759818072087603
RMSE: 0.4258406935461399

training loss
R^2: 0.8183073738057717
MAE: 0.27507562255446455
RMSE: 0.42586044787713556

penalty term: l1 ,learning rate: optimal ,batch size: 10
validation loss
R^2: 0.4183782745647113
MAE: 0.5263559576165668
RMSE: 0.7654517943540259

training loss
R^2: 0.4190991067482809
MAE: 0.5232827163966731
RMSE: 0.7614645288912191

penalty term: l2 ,learning rate: adaptive ,batch size: 100
validation loss
R^2: 0.8198470143059364
MAE: 0.28721062021630966
RMSE: 0.4260085027230229

training loss
R^2: 0.8193462119610894
MAE: 0.2861219815800056
RMSE: 0.42464126175028705

penalty term: l2 ,learning rate: invscaling ,batch size: 50
validation loss
R^2: 0.8611218322925468
MAE: 0.23665682134870697
RMSE: 0.374036964852156

training loss
R^2: 0.8609277776186577
MAE: 0.23536909245435642
RMSE: 0.37257941180746323

penalty term: None ,learning rate: invscaling ,batch size: 1
validation loss
R^2: 0.8613417809662796
MAE: 0.23694241174797143
RMSE: 0.37374065645848853

training loss
R^2: 0.8612751245309458
MAE: 0.23540837302929465
RMSE: 0.37211384358165556
```

Observation (Linear Regression with SGD): Stochastic Gradient Descent (SGD) was tested with different learning rates and batch sizes:

- Constant Learning Rate and ElasticNet Penalty with Batch Size 5:

The constant learning rate resulted in an RMSE of approximately 0.43, which is higher than the closed-form solution. This indicates room for improvement through hyperparameter tuning.

- Optimal Learning Rate and L1 Penalty with Batch Size 10:

The evaluation metrics suggest slight overfitting compared to other hyperparameter combinations. The high learning rate causes the model to converge too quickly, overshooting the optimal parameters, and leading to overfitting. The L1 penalty does not effectively prevent overfitting in this case.

- L2 Penalty, Adaptive Learning Rate, and Batch Size 100:

An RMSE of 0.45 indicates that, on average, the model's predictions are off by around 0.45 units. An R-squared value of 0.79 suggests the model fits the data poorly, explaining only a small portion of the variance in the target variable.

- L2 Penalty, Inverse Scaling Learning Rate, and Batch Size 50:

The inverse scaling learning rate is suitable for this dataset as it helps prevent overshooting optimal parameters early in training. A batch size of 50 is optimal for this dataset. The L2 penalty aids in preventing overfitting. Reducing the batch size further could lower the RMSE and improve results.

- No Penalty, Inverse Scaling Learning Rate, and Batch Size 1:

The combination of inverse scaling learning rate and smaller batch size yields the best results. In conclusion, the linear regression closed-form solution performs similarly to the SGD linear regression.

In [45]:
```
#Train model using polynomial regression(Closed form)

perform_pr(X_train,X_test, y_train,y_test)
```

```
validation loss
R^2: 0.8618734465803293
MAE: 0.23472431802629343
RMSE: 0.3730234400548633
```

Observation (Polynomial Regression closed form): Polynomial regression performing similar results as linear regression which indicates that there is not non-linear relationship in the data between labels and attributes.

In [31]:
```
#Train model using polynomial regression(SGD)

#Add polynomial features
X_train_poly,X_test_poly = add_poly(X_train,X_test)

perform_sgd(X_train_poly,y_train, X_test_poly, y_test,penalty='elasticnet',learn
perform_sgd(X_train_poly,y_train, X_test_poly, y_test,penalty='l1',learning_rate
perform_sgd(X_train_poly,y_train, X_test_poly, y_test,penalty='l2',learning_rate
perform_sgd(X_train_poly,y_train, X_test_poly, y_test)
```

```
penalty term: elasticnet ,learning rate: constant ,batch size: 5
validation loss
R^2: 0.7529718235629365
MAE: 0.34426288279339246
RMSE: 0.49885092452950097

training loss
R^2: 0.7519775572378036
MAE: 0.3434505955878878
RMSE: 0.4975584951429283

penalty term: l1 ,learning rate: optimal ,batch size: 10
validation loss
R^2: 0.44149617440093747
MAE: 0.5974101519594691
RMSE: 0.7500852257641194

training loss
R^2: 0.4383499725019444
MAE: 0.5960415040247149
RMSE: 0.7487408835882867

penalty term: l2 ,learning rate: adaptive ,batch size: 100
validation loss
R^2: 0.7166243163569255
MAE: 0.37059222362141403
RMSE: 0.534292189657923

training loss
R^2: 0.7155542041258195
MAE: 0.36870046826596714
RMSE: 0.5328419573720365

penalty term: None ,learning rate: invscaling ,batch size: 1
validation loss
R^2: 0.8600985739952701
MAE: 0.2348067862756657
RMSE: 0.3754123934605395

training loss
R^2: 0.8599459532809735
MAE: 0.23347162197104157
RMSE: 0.37389226984447904
```

Observation (polynomial regression SGD): Polynomial regression is performing similar way as linear regression. Seems like there no non-linear relationship between labels and attributes.

In case of polynomial regression, only invscaling learning rate and smallest batch size produces best results. Any other batch size more than 1 and learning rate like constant , optimal and adaptive is making the model overfitting to this dataset

In [32]:
```python
#Implement k fold with closed form using linear regression model
k_fold_closed(X_train, y_train)
```

```
Rank: 38
Rank: 38
Shape: (554456, 44)
[[-0.30161408 -0.30050529 -0.30153436 ...  0.83934123 -0.46484585
  -0.15134887]
 [ 3.31549508 -0.30050529 -0.30153436 ...  0.83934123 -0.42094524
  -0.15134887]
 [-0.30161408 -0.30050529 -0.30153436 ...  0.83934123 -0.95653276
  -0.15134887]
 ...
 [-0.30161408 -0.30050529 -0.30153436 ... -1.19141056 -0.90385202
  -0.15134887]
 [-0.30161408 -0.30050529 -0.30153436 ... -1.19141056 -0.39460487
  -0.15134887]
 [-0.30161408 -0.30050529 -0.30153436 ...  0.83934123 -0.01705956
  -0.15134887]]
[-0.23321071 -0.23446888 -0.23373629 -0.23450121]
```

Out[32]: 0.48371404086211867

In [33]:
```
#Implement k fold with sgd using linear regression model
k_fold_sgd(X_train,y_train)
```

```
[-0.23707516 -0.23135749 -0.23447338 -0.23431048]
```

Out[33]: 0.4840497184252309

Observation (K-fold linear regression): K-fold cross-validation with SGD is a more robust approach to evaluating the performance of a linear regression model than *a* standard linear regression model, but it can also increase the variance of the estimated performance, leading to a higher RMSE. In our case there is a large variation in the performance of the model across the folds. And hence k-fold rmse is higher than standard linear regression model rmse.

In [34]:
```
#Implement k fold with sgd using polynomial regression model

k_fold_closed(X_train_poly, y_train)
```

```
Rank: 39
Rank: 39
Shape: (554456, 72)
[[ 0.         -0.30203546 -0.3007894  ...  0.83934123 -0.46484585
  -0.15134887]
 [ 0.          3.31086954 -0.3007894  ...  0.83934123 -0.42094524
  -0.15134887]
 [ 0.         -0.30203546 -0.3007894  ...  0.83934123 -0.95653276
  -0.15134887]
 ...
 [ 0.         -0.30203546 -0.3007894  ... -1.19141056 -0.90385202
  -0.15134887]
 [ 0.         -0.30203546 -0.3007894  ... -1.19141056 -0.39460487
  -0.15134887]
 [ 0.         -0.30203546 -0.3007894  ...  0.83934123 -0.01705956
  -0.15134887]]
[-0.23383324 -0.23498186 -0.23500779 -0.23519671]
```

Out[34]: 0.4845151177275482

In [35]:
```
#Implement k fold with sgd using polynomial regression model
```

```
k_fold_sgd(X_train_poly,y_train)
```

```
[-0.23573872 -0.23503918 -0.23824596 -0.23602374]
```

Out[35]:
```
0.48606779140332806
```

Observation (K-fold polynomial regression):

K-fold linear regression is similar to k-fold polynomial regression. Both performing more or less same results with or without sgd.

Regularization Of Linear Model

In [36]:
```
perform_ridge(X_train,y_train,X_test,y_test,alpha=0.000000001)
perform_ridge(X_train,y_train,X_test,y_test,alpha=0.5)
perform_ridge(X_train,y_train,X_test,y_test,alpha=5)
perform_ridge(X_train,y_train,X_test,y_test,alpha=1000)
```

```
alpha: 1e-09
```

```
/usr/local/lib/python3.8/dist-packages/sklearn/linear_model/_ridge.py:157: LinAlg
Warning: Ill-conditioned matrix (rcond=8.11893e-17): result may not be accurate.
  return linalg.solve(A, Xy, sym_pos=True, overwrite_a=True).T
```

```
Validation loss
R^2: 0.8619328466937523
MAE: 0.23507085486191912
RMSE: 0.3729432236996928

training loss
R^2: 0.8618280642814838
MAE: 0.23366171220256404
RMSE: 0.37137150384396084

alpha: 0.5
Validation loss
R^2: 0.8619328428283652
MAE: 0.23507090477262857
RMSE: 0.3729432289202318

training loss
R^2: 0.8618280642808281
MAE: 0.23366176018319768
RMSE: 0.371371503844842

alpha: 5
Validation loss
R^2: 0.8619328079813877
MAE: 0.23507135396945758
RMSE: 0.37294327598408006

training loss
R^2: 0.8618280642159064
MAE: 0.23366219211031075
RMSE: 0.3713715039320888

alpha: 1000
Validation loss
R^2: 0.8619225286208837
MAE: 0.23517457238531597
RMSE: 0.37295715888766123

training loss
R^2: 0.8618254523243127
MAE: 0.2337614301973292
RMSE: 0.3713750139702158
```

Observation (ridge): Ridge regression in not improving the performance significantly. But seems like it resulting a model with minimum rmse than any other combination

In [37]:
```
#Perform Regularization(Lasso)

perform_l(X_train, y_train,X_test,y_test,alpha=0.0000000001)
perform_l(X_train, y_train,X_test,y_test,alpha=0.1)
perform_l(X_train, y_train,X_test,y_test,alpha=5)
perform_l(X_train, y_train,X_test,y_test,alpha=100)
```

```
/usr/local/lib/python3.8/dist-packages/sklearn/linear_model/_coordinate_descent.p
y:647: ConvergenceWarning: Objective did not converge. You might want to increase
the number of iterations, check the scale of the features or consider increasing
regularisation. Duality gap: 6.622e+03, tolerance: 5.534e+01
  model = cd_fast.enet_coordinate_descent(
```

```
alpha: 1e-10
validation loss
R^2: 0.861932846693331
MAE: 0.23507085485754492
RMSE: 0.3729432237002618

training loss
R^2: 0.8618280642814841
MAE: 0.23366171219721604
RMSE: 0.3713715038439606

alpha: 0.1
validation loss
R^2: 0.7579664691277564
MAE: 0.38277903411940556
RMSE: 0.49378205579517426

training loss
R^2: 0.7580312395475854
MAE: 0.38110373036219736
RMSE: 0.49144882971320697

alpha: 5
validation loss
R^2: -2.6180229866223925e-06
MAE: 0.8008473084119796
RMSE: 1.0036865484802193

training loss
R^2: 0.0
MAE: 0.7973463512345691
RMSE: 0.9990762967096172

alpha: 100
validation loss
R^2: -2.6180229866223925e-06
MAE: 0.8008473084119796
RMSE: 1.0036865484802193

training loss
R^2: 0.0
MAE: 0.7973463512345691
RMSE: 0.9990762967096172
```

Observation (Lasso): Lasso regression is not really improving the performance, It is actually decreasing with increasing value of alpha. for smaller value of alpha the results are more or less similar

In [38]:

```
#Perform Regularization(Elastic net)

perform_en(X_train, y_train,X_test,y_test,alpha=0.0000000001,l1=0.5)
perform_en(X_train, y_train,X_test,y_test,alpha=0.1,l1=0.8)
perform_en(X_train, y_train,X_test,y_test,alpha=5,l1=0.5)
perform_en(X_train, y_train,X_test,y_test,alpha=100,l1=0.2)
```

```
/usr/local/lib/python3.8/dist-packages/sklearn/linear_model/_coordinate_descent.py:647: ConvergenceWarning: Objective did not converge. You might want to increase the number of iterations, check the scale of the features or consider increasing regularisation. Duality gap: 6.647e+03, tolerance: 5.534e+01
  model = cd_fast.enet_coordinate_descent(
alpha: 1e-10 ,l1 ratio: 0.5
validation loss
R^2: 0.8619328466933547
MAE: 0.2350708548623474
RMSE: 0.37294322370022975

alpha: 1e-10 ,l1 ratio: 0.5
training loss
R^2: 0.861828064281484
MAE: 0.2336617122024007
RMSE: 0.37137150384396067

alpha: 0.1 ,l1 ratio: 0.8
validation loss
R^2: 0.7867655674570522
MAE: 0.35012721582295053
RMSE: 0.4634748820668961

alpha: 0.1 ,l1 ratio: 0.8
training loss
R^2: 0.7868509241562686
MAE: 0.348479899743694
RMSE: 0.4612542516910213

alpha: 5 ,l1 ratio: 0.5
validation loss
R^2: -2.6180229866223925e-06
MAE: 0.8008473084119796
RMSE: 1.0036865484802193

alpha: 5 ,l1 ratio: 0.5
training loss
R^2: 0.0
MAE: 0.7973463512345691
RMSE: 0.9990762967096172

alpha: 100 ,l1 ratio: 0.2
validation loss
R^2: -2.6180229866223925e-06
MAE: 0.8008473084119796
RMSE: 1.0036865484802193

alpha: 100 ,l1 ratio: 0.2
training loss
R^2: 0.0
MAE: 0.7973463512345691
RMSE: 0.9990762967096172
```

Observation(elastic net): Elasticnet is behaving similar like lasso regression. Performance is getting worse at increase value of alpha.

Regularization of Polynomial Model

In [39]:

```
#Perform Regularization(Ridge)
perform_ridge(X_train_poly,y_train,X_test_poly,y_test,alpha=0)
perform_ridge(X_train_poly,y_train,X_test_poly,y_test,alpha=0.000000001)
perform_ridge(X_train_poly,y_train,X_test_poly,y_test,alpha=0.5)
perform_ridge(X_train_poly,y_train,X_test_poly,y_test,alpha=5)
perform_ridge(X_train_poly,y_train,X_test_poly,y_test,alpha=1000)
```

```
alpha: 0
Validation loss
R^2: -1.3000024577896782e+21
MAE: 24034731741.192627
RMSE: 36188419988.406746

training loss
R^2: 0.8611920571663053
MAE: 0.23439072591390045
RMSE: 0.37222523633068266

alpha: 1e-09
Validation loss
R^2: 0.8619329789515859
MAE: 0.23507161111378627
RMSE: 0.3729430450740259

training loss
R^2: 0.861828064281484
MAE: 0.2336617122025647
RMSE: 0.3713715038439607

alpha: 0.5
Validation loss
R^2: 0.8619329481501055
MAE: 0.23507167698979428
RMSE: 0.37294308667410253

training loss
R^2: 0.8618280642808309
MAE: 0.23366176079273718
RMSE: 0.37137150384483825

alpha: 5
Validation loss
R^2: 0.8619329128611364
MAE: 0.2350721316003453
RMSE: 0.37294313433491666

training loss
R^2: 0.8618280642161844
MAE: 0.23366219820667705
RMSE: 0.37137150393171514

alpha: 1000
Validation loss
R^2: 0.8619225489597883
MAE: 0.23517654978778746
RMSE: 0.3729571314192398

training loss
R^2: 0.8618254629282518
MAE: 0.23376265689273606
RMSE: 0.37137499971998594
```

Observation: Ridge regression is not improving performance significantly in polynomial linear regression. The rmse is reducing with increasing alpha.

In [40]:
```python
#Perform Regularization(Lasso)

perform_l(X_train_poly,y_train,X_test_poly,y_test,alpha=0.0000000001)
perform_l(X_train_poly,y_train,X_test_poly,y_test,alpha=0.1)
perform_l(X_train_poly,y_train,X_test_poly,y_test,alpha=5)
perform_l(X_train_poly,y_train,X_test_poly,y_test,alpha=100)
```

```
/usr/local/lib/python3.8/dist-packages/sklearn/linear_model/_coordinate_descent.p
y:647: ConvergenceWarning: Objective did not converge. You might want to increase
the number of iterations, check the scale of the features or consider increasing
regularisation. Duality gap: 9.474e+03, tolerance: 5.534e+01
  model = cd_fast.enet_coordinate_descent(
alpha: 1e-10
validation loss
R^2: 0.8619330734165542
MAE: 0.23507071253164294
RMSE: 0.3729429174908469

training loss
R^2: 0.861828064281484
MAE: 0.23366171220311557
RMSE: 0.37137150384396067

alpha: 0.1
validation loss
R^2: 0.7579664691277564
MAE: 0.38277903411940556
RMSE: 0.49378205579517426

training loss
R^2: 0.7580312395475854
MAE: 0.38110373036219736
RMSE: 0.49144882971320697

alpha: 5
validation loss
R^2: -2.6180229866223925e-06
MAE: 0.8008473084119796
RMSE: 1.0036865484802193

training loss
R^2: 0.0
MAE: 0.7973463512345691
RMSE: 0.9990762967096172

alpha: 100
validation loss
R^2: -2.6180229866223925e-06
MAE: 0.8008473084119796
RMSE: 1.0036865484802193

training loss
R^2: 0.0
MAE: 0.7973463512345691
RMSE: 0.9990762967096172
```

observation: lasso is behaving similarly with polynomial regression as linear regression.

In [41]:
```
#Perform Regularization(Elastic net)

perform_en(X_train_poly,y_train,X_test_poly,y_test,alpha=0.0000000001,l1=0.5)
perform_en(X_train_poly,y_train,X_test_poly,y_test,alpha=0.1,l1=0.8)
perform_en(X_train_poly,y_train,X_test_poly,y_test,alpha=5,l1=0.5)
perform_en(X_train_poly,y_train,X_test_poly,y_test,alpha=100,l1=0.2)
```

```
/usr/local/lib/python3.8/dist-packages/sklearn/linear_model/_coordinate_descent.p
y:647: ConvergenceWarning: Objective did not converge. You might want to increase
the number of iterations, check the scale of the features or consider increasing
regularisation. Duality gap: 9.460e+03, tolerance: 5.534e+01
  model = cd_fast.enet_coordinate_descent(
```

```
alpha: 1e-10 ,l1 ratio: 0.5
validation loss
R^2: 0.8619330734166257
MAE: 0.23507071250305533
RMSE: 0.3729429174907503

alpha: 1e-10 ,l1 ratio: 0.5
training loss
R^2: 0.861828064281484
MAE: 0.23366171220539525
RMSE: 0.37137150384396067

alpha: 0.1 ,l1 ratio: 0.8
validation loss
R^2: 0.7867655674455376
MAE: 0.35012721583410494
RMSE: 0.46347488207940984

alpha: 0.1 ,l1 ratio: 0.8
training loss
R^2: 0.786850924145734
MAE: 0.34847989975420385
RMSE: 0.4612542517024197

alpha: 5 ,l1 ratio: 0.5
validation loss
R^2: -2.6180229866223925e-06
MAE: 0.8008473084119796
RMSE: 1.0036865484802193

alpha: 5 ,l1 ratio: 0.5
training loss
R^2: 0.0
MAE: 0.7973463512345691
RMSE: 0.9990762967096172

alpha: 100 ,l1 ratio: 0.2
validation loss
R^2: -2.6180229866223925e-06
MAE: 0.8008473084119796
RMSE: 1.0036865484802193

alpha: 100 ,l1 ratio: 0.2
training loss
R^2: 0.0
MAE: 0.7973463512345691
RMSE: 0.9990762967096172
```

observation: elastic net is also similar with polynomial regression as it is with linear regression.

In [ ]:

```
```

Final Observation

There is not much difference in model performance metrics with different hyperparameter combinations; the RMSE is similar across the dataset. Both linear and polynomial regression models perform similarly. The performance of SGD and the closed-form solution is also comparable for this dataset. Although K-fold cross-validation yields a robust model, it exhibits high variability due to the dataset's diversity.

I would go with ridge regression linear model as my final model for this dataset.

In [46]:
```
rdg = Ridge(alpha = 0.000000000000000001)
print("alpha:",0.000000000000000001)
rdg.fit(X_train, y_train)
pred_test_rr= rdg.predict(X_test)
```

```
alpha: 1e-18
```

Scaled predicted values of price for uber and lyft dataset:

In [48]:
```
print(pred_test_rr)
```

```
[[-0.73213572]
 [-0.19163039]
 [-0.1027623 ]
 ...
 [ 1.37847291]
 [ 1.43721421]
 [-0.89270137]]
```

Future Exploration

We can explore GridSearchCV to find the optimal hyperparameters. GridSearchCV exhaustively searches over a pre-defined hyperparameter space, evaluating the model's performance with each combination of hyperparameters. Using GridSearchCV returns the best possible hyperparameters, which will help us achieve the best performing model.