```
In [1]:
          import pandas as pd
           import warnings
          warnings.filterwarnings("ignore")
In [2]:
          data=pd.read csv("/home/placement/Downloads/fiat500.csv")
In [3]:
          data.describe()
Out[3]:
                           ID engine_power
                                             age_in_days
                                                                    km previous_owners
                                                                                                  lat
                                                                                                              lon
                                                                                                                          price
           count 1538.000000
                                1538.000000
                                             1538.000000
                                                            1538.000000
                                                                             1538.000000 1538.000000
                                                                                                      1538.000000
                                                                                                                    1538.000000
                   769.500000
                                  51.904421
                                             1650.980494
                                                           53396.011704
                                                                                1.123537
                                                                                            43.541361
                                                                                                        11.563428
                                                                                                                    8576.003901
           mean
                                                                                                         2.328190
              std
                   444.126671
                                   3.988023
                                              1289.522278
                                                           40046.830723
                                                                                0.416423
                                                                                             2.133518
                                                                                                                    1939.958641
             min
                     1.000000
                                   51.000000
                                              366.000000
                                                            1232.000000
                                                                                1.000000
                                                                                            36.855839
                                                                                                         7.245400
                                                                                                                    2500.000000
             25%
                   385.250000
                                   51.000000
                                              670.000000
                                                                                1.000000
                                                                                            41.802990
                                                                                                         9.505090
                                                                                                                    7122.500000
                                                           20006.250000
             50%
                   769.500000
                                  51.000000
                                             1035.000000
                                                           39031.000000
                                                                                1.000000
                                                                                           44.394096
                                                                                                        11.869260
                                                                                                                    9000.000000
             75%
                  1153.750000
                                  51.000000
                                             2616.000000
                                                           79667.750000
                                                                                1.000000
                                                                                            45.467960
                                                                                                        12.769040
                                                                                                                  10000.000000
             max 1538.000000
                                  77.000000
                                             4658.000000
                                                          235000.000000
                                                                                4.000000
                                                                                            46.795612
                                                                                                        18.365520
                                                                                                                  11100.000000
          data.head()
In [4]:
Out[4]:
                  model engine_power age_in_days
                                                        km previous_owners
                                                                                              lon price
                                                                                    lat
           0
               1
                  lounge
                                    51
                                               882
                                                      25000
                                                                           1 44.907242
                                                                                         8.611560
                                                                                                  8900
               2
           1
                    pop
                                    51
                                               1186
                                                      32500
                                                                           1 45.666359 12.241890
                                                                                                  8800
               3
                   sport
                                    74
                                               4658
                                                    142228
                                                                             45.503300
                                                                                       11.417840
                                                                                                  4200
                                    51
                                               2739
                                                    160000
                                                                             40.633171 17.634609
                                                                                                  6000
                  lounge
                                    73
                                               3074
                                                    106880
                                                                          1 41.903221 12.495650
                                                                                                  5700
               5
                    pop
```

In [5]: data1=data.drop(['lat','lon','ID'],axis=1)

In [6]: data1

Out[6]:

	model	engine_power	age_in_days	km	previous_owners	price
0	lounge	51	882	25000	1	8900
1	pop	51	1186	32500	1	8800
2	sport	74	4658	142228	1	4200
3	lounge	51	2739	160000	1	6000
4	pop	73	3074	106880	1	5700
1533	sport	51	3712	115280	1	5200
1534	lounge	74	3835	112000	1	4600
1535	pop	51	2223	60457	1	7500
1536	lounge	51	2557	80750	1	5990
1537	pop	51	1766	54276	1	7900

1538 rows × 6 columns

In [7]: data.shape

Out[7]: (1538, 9)

In [8]: data1=data.drop(['lat','lon','ID'],axis=1)

In [9]: data1

Out[9]:

	model	engine_power	age_in_days	km	previous_owners	price
0	lounge	51	882	25000	1	8900
1	pop	51	1186	32500	1	8800
2	sport	74	4658	142228	1	4200
3	lounge	51	2739	160000	1	6000
4	pop	73	3074	106880	1	5700
1533	sport	51	3712	115280	1	5200
1534	lounge	74	3835	112000	1	4600
1535	pop	51	2223	60457	1	7500
1536	lounge	51	2557	80750	1	5990
1537	рор	51	1766	54276	1	7900

1538 rows × 6 columns

```
In [10]: data1.shape
```

Out[10]: (1538, 6)

In [11]: data1=pd.get_dummies(data1)

In [12]: data1

Out[12]:

	engine_power	age_in_days	km	previous_owners	price	model_lounge	model_pop	model_sport
0	51	882	25000	1	8900	1	0	0
1	51	1186	32500	1	8800	0	1	0
2	74	4658	142228	1	4200	0	0	1
3	51	2739	160000	1	6000	1	0	0
4	73	3074	106880	1	5700	0	1	0
1533	51	3712	115280	1	5200	0	0	1
1534	74	3835	112000	1	4600	1	0	0
1535	51	2223	60457	1	7500	0	1	0
1536	51	2557	80750	1	5990	1	0	0
1537	51	1766	54276	1	7900	0	1	0

1538 rows × 8 columns

```
In [13]: y=datal['price']
x=datal.drop('price',axis=1)
```

```
In [14]: y
Out[14]: 0
                     8900
                     8800
           2
                     4200
            3
                     6000
            4
                     5700
           1533
                     5200
           1534
                     4600
           1535
                     7500
           1536
                     5990
           1537
                     7900
           Name: price, Length: 1538, dtype: int64
In [15]: from sklearn.model_selection import train_test_split
    x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.33,random_state=42)
```

In [16]: data1=data.loc[(data.model=="lounge")]
 data1

Out[16]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	lon	price
0	1	lounge	51	882	25000	1	44.907242	8.611560	8900
3	4	lounge	51	2739	160000	1	40.633171	17.634609	6000
6	7	lounge	51	731	11600	1	44.907242	8.611560	10750
7	8	lounge	51	1521	49076	1	41.903221	12.495650	9190
11	12	lounge	51	366	17500	1	45.069679	7.704920	10990
1528	1529	lounge	51	2861	126000	1	43.841980	10.515310	5500
1529	1530	lounge	51	731	22551	1	38.122070	13.361120	9900
1530	1531	lounge	51	670	29000	1	45.764648	8.994500	10800
1534	1535	lounge	74	3835	112000	1	45.845692	8.666870	4600
1536	1537	lounge	51	2557	80750	1	45.000702	7.682270	5990

1094 rows × 9 columns

In [17]: x_train.shape

Out[17]: (1030, 7)

```
In [18]: y train
Out[18]: 527
                  9990
         129
                  9500
         602
                  7590
         331
                  8750
         323
                  9100
         1130
                 10990
         1294
                  9800
         860
                  5500
         1459
                  9990
         1126
                  8900
         Name: price, Length: 1030, dtype: int64
In [19]: y test.head(5)
Out[19]: 481
                 7900
                 7900
         76
                 9400
         1502
         669
                 8500
                 9700
         1409
         Name: price, dtype: int64
In [20]: y train.shape
Out[20]: (1030,)
In [21]: #ridge regression
         from sklearn.model selection import GridSearchCV
         from sklearn.linear model import Ridge
         alpha=[1e-15,1e-10,1e-8,1e-4,1e-3,1e-2,1,5,10,20,30]
         ridge=Ridge()
         parameters={'alpha':alpha}
         ridge regressor=GridSearchCV(ridge,parameters)
         ridge regressor.fit(x train,y train)
Out[21]: GridSearchCV(estimator=Ridge(),
                      param grid={'alpha': [1e-15, 1e-10, 1e-08, 0.0001, 0.001, 0.01, 1,
                                             5, 10, 20, 30]})
```

```
In [22]: ridge_regressor.best_params_
Out[22]: {'alpha': 30}
In [23]: ridge=Ridge(alpha=30)
    ridge.fit(x_train,y_train)
    y_pred_ridge=ridge.predict(x_test)

In [24]: from sklearn.metrics import mean_squared_error
    Ridge_Error=mean_squared_error(y_pred_ridge,y_test)
    Ridge_Error

Out[24]: 579521.7970897449

In [25]: from sklearn.metrics import r2_score
    r2_score(y_test,y_pred_ridge)
Out[25]: 0.8421969385523054
```

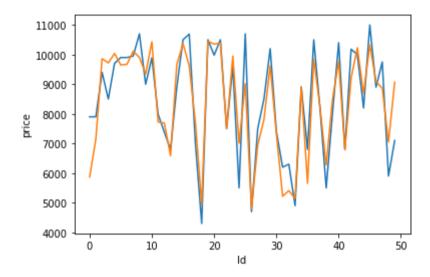
```
In [26]: Results=pd.DataFrame(columns=['price','predicted'])
    Results['price']=y_test
    Results['predicted']=y_pred_ridge
    Results=Results.reset_index()
    Results['Id']=Results.index
    Results.head(15)
```

Out[26]:

	index	price	predicted	ld
0	481	7900	5869.741155	0
1	76	7900	7149.563327	1
2	1502	9400	9862.785355	2
3	669	8500	9719.283532	3
4	1409	9700	10035.895686	4
5	1414	9900	9650.311090	5
6	1089	9900	9669.183317	6
7	1507	9950	10115.128380	7
8	970	10700	9900.241944	8
9	1198	8999	9347.080772	9
10	1088	9890	10431.237961	10
11	576	7990	7725.756431	11
12	965	7380	7691.089846	12
13	1488	6800	6583.674680	13
14	1432	8900	9659.240069	14

```
In [27]: import seaborn as sns
import matplotlib.pyplot as plt
sns.lineplot(x='Id',y='price',data=Results.head(50))
sns.lineplot(x='Id',y='predicted',data=Results.head(50))
plt.plot()
```

Out[27]: []



In []: