```
In [23]: import pandas as pd
In [24]: data=pd.read_csv("fiat500 (1).csv")
In [25]: data
Out[25]:
                   ID model engine_power age_in_days
                                                           km previous_owners
                                                                                      lat
                                                                                               lon price
               0
                                        51
                                                   882
                                                         25000
                                                                             1 44.907242
                                                                                          8.611560
                                                                                                    8900
                    1 lounge
                                                         32500
                                                                             1 45.666359 12.241890
               1
                                        51
                                                  1186
                                                                                                    8800
                          pop
               2
                         sport
                                        74
                                                  4658
                                                       142228
                                                                             1 45.503300 11.417840
                                                                                                    4200
                                                       160000
                                                                             1 40.633171 17.634609
               3
                       lounge
                                        51
                                                  2739
                                                                                                    6000
                                        73
                                                  3074
                                                        106880
                                                                             1 41.903221 12.495650
                                                                                                    5700
                          pop
            1533
                                                  3712 115280
                                                                             1 45.069679
                                                                                          7.704920
                                                                                                    5200
                 1534
                         sport
                                        51
                                                        112000
            1534
                 1535
                       lounge
                                        74
                                                  3835
                                                                             1 45.845692
                                                                                          8.666870
                                                                                                    4600
            1535 1536
                                        51
                                                  2223
                                                         60457
                                                                             1 45.481541
                                                                                          9.413480
                                                                                                    7500
                          pop
                                        51
            1536
                 1537
                       lounge
                                                  2557
                                                         80750
                                                                             1 45.000702
                                                                                          7.682270
                                                                                                    5990
            1537 1538
                          pop
                                        51
                                                  1766
                                                         54276
                                                                             1 40.323410 17.568270
                                                                                                    7900
           1538 rows × 9 columns
In [26]: | data=data.drop(['lat','lon','ID',],axis=1)
```

In [27]: data

Out[27]:

	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 [46]: # ridge regression

In [47]: 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[47]: GridSearchCV(estimator=Ridge(),
                       param grid={'alpha': [1e-15, 1e-10, 1e-08, 0.0001, 0.001, 0.01, 1,
                                               5, 10, 20, 301})
         In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
         On GitHub, the HTML representation is unable to render, please try loading this page with nbyiewer.org.
In [48]: ridge regressor.best params
Out[48]: {'alpha': 30}
In [49]: ridge=Ridge(alpha=30)
          ridge.fit(X train,y train)
         y pred ridge=ridge.predict(X test)
In [50]: Ridge Error=mean squared error(y pred ridge,y test)
         Ridge Error
Out[50]: 579521.7970897449
In [51]: from sklearn.metrics import r2 score
         r2 score(y test,ypred)
Out[51]: 0.8415526986865394
```

```
In [52]: 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(25)
```

Out[52]:

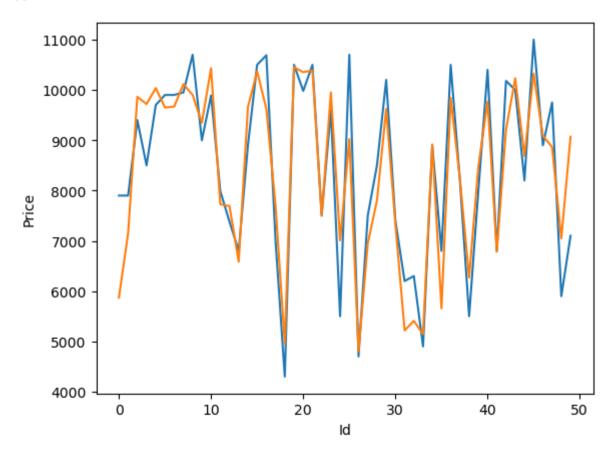
	index	Price	Predicted	ld
0	481	7900	5869.741155	0
1	76	7900	7149.563327	1
2	1502	9400	9862.785355	2
3	669	8500	9719.283532	3
4	1409	9700	10035.895686	4
5	1414	9900	9650.311090	5
6	1089	9900	9669.183317	6
7	1507	9950	10115.128380	7
8	970	10700	9900.241944	8
9	1198	8999	9347.080772	9
10	1088	9890	10431.237961	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
15	380	10500	10370.231518	15
16	754	10690	9620.427488	16
17	30	6990	7689.189244	17
18	49	4300	4954.595074	18
19	240	10500	10452.262871	19
20	344	9980	10353.107796	20

	index	Price	Predicted	ld
21	354	10500	10388.635632	21
22	124	7500	7503.302407	22
23	383	9600	9948.970588	23
24	1389	5500	7009.047336	24

```
In [53]: 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[53]: []



In [54]: # *Elastic*

```
In [55]: import pandas as pd
           import warnings
           warnings.filterwarnings("ignore")
In [56]: data=pd.read_csv("fiat500 (1).csv")
In [57]: data
Out[57]:
                   ID model engine_power age_in_days
                                                          km previous_owners
                                                                                             lon price
                                                                                    lat
               0
                    1 lounge
                                       51
                                                   882
                                                        25000
                                                                            1 44.907242
                                                                                         8.611560
                                                                                                  8900
                                                  1186
                                                        32500
                                                                            1 45.666359 12.241890
                                                                                                  8800
              1
                    2
                         pop
                                       51
               2
                                       74
                                                  4658
                                                      142228
                                                                            1 45.503300 11.417840
                                                                                                  4200
                        sport
                                                      160000
               3
                                                  2739
                                                                            1 40.633171 17.634609
                    4 lounge
                                       51
                                                                                                  6000
                         pop
                                       73
                                                  3074
                                                       106880
                                                                            1 41.903221 12.495650
                                                                                                  5700
            1533
                                       51
                                                  3712 115280
                                                                            1 45.069679
                                                                                         7.704920
                                                                                                  5200
                 1534
                        sport
                                                      112000
            1534
                 1535
                      lounge
                                       74
                                                  3835
                                                                            1 45.845692
                                                                                         8.666870
                                                                                                  4600
            1535
                 1536
                         pop
                                       51
                                                  2223
                                                        60457
                                                                            1 45.481541
                                                                                         9.413480
                                                                                                  7500
            1536
                 1537
                       lounge
                                       51
                                                  2557
                                                        80750
                                                                            1 45.000702
                                                                                         7.682270
                                                                                                  5990
            1537 1538
                                                  1766
                                                                            1 40.323410 17.568270
                         pop
                                       51
                                                        54276
                                                                                                  7900
           1538 rows × 9 columns
In [58]: | data=data.loc[(data.previous_owners==1)]
```

In [59]: data

Out[59]:

	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
1	2	рор	51	1186	32500	1	45.666359	12.241890	8800
2	3	sport	74	4658	142228	1	45.503300	11.417840	4200
3	4	lounge	51	2739	160000	1	40.633171	17.634609	6000
4	5	рор	73	3074	106880	1	41.903221	12.495650	5700
1533	1534	sport	51	3712	115280	1	45.069679	7.704920	5200
1534	1535	lounge	74	3835	112000	1	45.845692	8.666870	4600
1535	1536	pop	51	2223	60457	1	45.481541	9.413480	7500
1536	1537	lounge	51	2557	80750	1	45.000702	7.682270	5990
1537	1538	pop	51	1766	54276	1	40.323410	17.568270	7900

1389 rows × 9 columns

```
In [60]: data=data.drop(['ID','lat','lon'],axis=1)
```

Tn	[61]		data
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	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

1389 rows × 6 columns

```
In [62]: data=pd.get_dummies(data)
In [63]: data.shape
Out[63]: (1389, 8)
In [64]: y=data['price']
x=data.drop('price',axis=1)
```

```
In [65]: y
Out[65]: 0
                   8900
                   8800
          2
                   4200
          3
                   6000
                   5700
          4
                   . . .
          1533
                   5200
          1534
                   4600
          1535
                   7500
          1536
                   5990
          1537
                   7900
          Name: price, Length: 1389, dtype: int64
In [66]: from sklearn.model_selection import train_test_split
          X_train,X_test,y_train,y_test=train_test_split(x,y,test_size=0.1,random_state=42)
In [67]: X_test.head(5)
Out[67]:
                                         km previous_owners model_lounge model_pop model_sport
               engine_power age_in_days
                        51
                                 3347 148000
                                                                      1
                                                                                0
                                                                                           0
           625
                                                         1
           187
                                      117000
                        51
                                 4322
                                                         1
                                                                      1
                                                                                0
                                                                                           0
           279
                        51
                                 4322
                                      120000
                                                         1
                                                                      0
                                                                                1
                                                                                           0
           734
                        51
                                  974
                                       12500
                                                         1
                                                                      0
                                                                                1
                                                                                           0
                        51
           315
                                 1096
                                       37000
                                                         1
                                                                      1
                                                                                0
                                                                                           0
```

```
In [68]: from sklearn.model selection import GridSearchCV
         from sklearn.linear model import ElasticNet
         elastic = ElasticNet()
         parameters = { 'alpha': [1e-15, 1e-10, 1e-8, 1e-4, 1e-3,1e-2, 1, 5, 10, 20]}
         elastic regressor = GridSearchCV(elastic, parameters)
         elastic regressor.fit(X train, y train)
Out[68]: GridSearchCV(estimator=ElasticNet(),
                       param grid={'alpha': [1e-15, 1e-10, 1e-08, 0.0001, 0.001, 0.01, 1,
                                              5, 10, 201})
         In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
         On GitHub, the HTML representation is unable to render, please try loading this page with nbyiewer.org.
In [69]: elastic regressor.best params
Out[69]: {'alpha': 0.01}
In [70]: elastic=ElasticNet(alpha=0.01)
         elastic.fit(X train,y train)
         v pred elastic=elastic.predict(X_test)
In [71]: from sklearn.metrics import r2 score
         r2_score(y_test,y_pred_elastic)
Out[71]: 0.8488682857174344
In [72]: from sklearn.metrics import mean squared error
         elastic Error=mean squared error(y pred elastic,y test)
         elastic Error
Out[72]: 603966.023413073
```

```
In [73]: Results= pd.DataFrame(columns=['Price','Predicted'])
    Results['Price']=y_test
    Results['Predicted']=y_pred_elastic
    Results=Results.reset_index()
    Results['Id']=Results.index
    Results.head(25)
```

Out[73]:

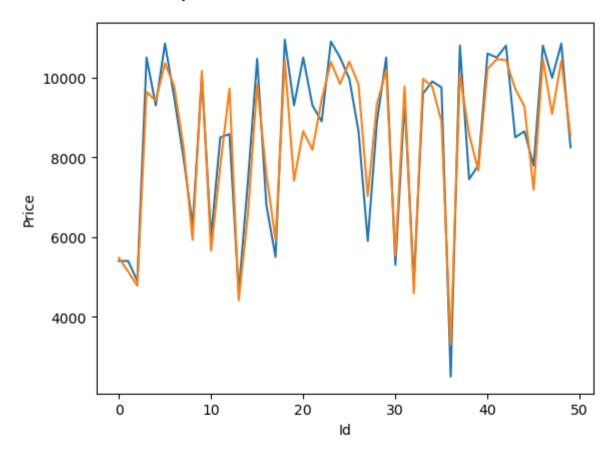
	index	Price	Predicted	ld
0	625	5400	5477.052458	0
1	187	5399	5137.435504	1
2	279	4900	4778.564980	2
3	734	10500	9640.895436	3
4	315	9300	9415.174300	4
5	652	10850	10356.323449	5
6	1472	9500	9781.272728	6
7	619	7999	8276.238400	7
8	992	6300	5925.267808	8
9	1154	10000	10158.433547	9
10	757	6000	5654.915390	10
11	1299	8500	7779.899617	11
12	400	8580	9724.510940	12
13	314	4600	4411.587148	13
14	72	7400	6568.196031	14
15	265	10470	9832.106012	15
16	800	6800	7576.247388	16
17	116	5500	5921.661919	17
18	181	10950	10422.823376	18
19	564	9300	7412.883090	19
20	1008	10500	8656.046516	20

	index	Price	Predicted	ld
21	1035	9300	8184.755615	21
22	1194	8900	9448.594403	22
23	131	10900	10388.473661	23
24	688	10499	9836.026696	24

```
In [74]: 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))
```

Out[74]: <Axes: xlabel='Id', ylabel='Price'>



In []: