```
import pandas as pd
In [1]:
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
                                                                                          1538.000000
                                                                                                      1538.000000
                                                                                                                    1538.000000
            count 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
                    385.250000
                                   51.000000
                                                                                                          9.505090
                                                                                                                    7122.500000
             25%
                                               670.000000
                                                            20006.250000
                                                                                1.000000
                                                                                            41.802990
             50%
                    769.500000
                                   51.000000
                                              1035.000000
                                                            39031.000000
                                                                                1.000000
                                                                                            44.394096
                                                                                                         11.869260
                                                                                                                    9000.000000
                                                            79667.750000
             75%
                  1153.750000
                                   51.000000
                                              2616.000000
                                                                                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
```

In [4]: data1=data.loc[(data.previous_owners==1)]

In [5]: data1

Out[5]:

	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	pop	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	pop	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 [8]: data2

Out[8]:

	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 [9]: data3=pd.get_dummies(data2)

In [10]: data3

Out[10]:

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

1389 rows × 8 columns

```
In [11]: y=data3['price']
x=data3.drop('price',axis=1)
```

```
In [12]: y
Out[12]: 0
                 8900
                 8800
                 4200
         2
         3
                 6000
                 5700
         4
                 . . .
         1533
                 5200
         1534
                 4600
         1535
                 7500
         1536
                 5990
         1537
                 7900
         Name: price, Length: 1389, dtype: int64
```

In [13]: x

Out[13]:

	engine_power	age_in_days	km	previous_owners	model_lounge	model_pop	model_sport
0	51	882	25000	1	1	0	0
1	51	1186	32500	1	0	1	0
2	74	4658	142228	1	0	0	1
3	51	2739	160000	1	1	0	0
4	73	3074	106880	1	0	1	0
1533	51	3712	115280	1	0	0	1
1534	74	3835	112000	1	1	0	0
1535	51	2223	60457	1	0	1	0
1536	51	2557	80750	1	1	0	0
1537	51	1766	54276	1	0	1	0

1389 rows × 7 columns

In [14]: 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)
 x_test.head(5)

Out[14]:

	engine_power	age_in_days	km	previous_owners	model_lounge	model_pop	model_sport
625	51	3347	148000	1	1	0	0
187	51	4322	117000	1	1	0	0
279	51	4322	120000	1	0	1	0
734	51	974	12500	1	0	1	0
315	51	1096	37000	1	1	0	0

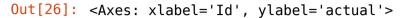
```
In [15]: import warnings
         warnings.filterwarnings("ignore")
In [16]: from sklearn.model selection import GridSearchCV
         from sklearn.linear model import ElasticNet
         elastic = ElasticNet()
         parameters = {'alpha': [1e-15, 1e-10, 1e-8, 1e-4, 1e-3,1e-2, 1, 5, 10, 20]}
         elastic regressor = GridSearchCV(elastic, parameters)
         elastic regressor.fit(x train, y train)
Out[16]:
                GridSearchCV
          ▶ estimator: ElasticNet
                ▶ ElasticNet
In [17]: elastic regressor.best params
Out[17]: {'alpha': 0.01}
In [18]: elastic=ElasticNet(alpha=30)
In [19]: elastic.fit(x train,y train)
         y pred elastic=elastic.predict(x test)
In [21]: from sklearn.metrics import mean squared error
         ElasticNet Error=mean squared error(y pred elastic, y test)
         ElasticNet Error
Out[21]: 532100.3330996548
In [22]: from sklearn.metrics import r2 score
         r2 score(y test,y pred elastic)
Out[22]: 0.8556728612765546
```

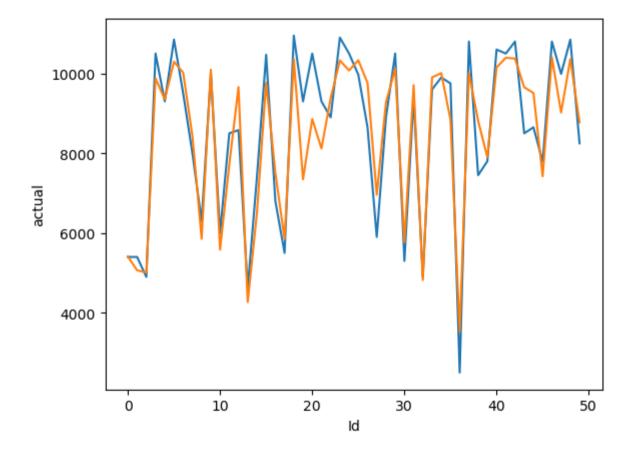
```
In [23]: results=pd.DataFrame(columns=['actual','Predicted'])
    results['actual']=y_test
    results['Predicted']=y_pred_elastic
    results=results.reset_index()
    results['Id']=results.index
    results.head(10)
```

Out[23]:

	index	actual	Predicted	ld
0	625	5400	5407.555124	0
1	187	5399	5065.234663	1
2	279	4900	5009.102898	2
3	734	10500	9879.757396	3
4	315	9300	9351.099924	4
5	652	10850	10294.094950	5
6	1472	9500	10020.794018	6
7	619	7999	8432.019194	7
8	992	6300	5854.256872	8
9	1154	10000	10095.297228	9

In [26]: import seaborn as sns
import matplotlib.pyplot as plt
sns.lineplot(x='Id',y='actual',data=results.head(50)) #red is actual
sns.lineplot(x='Id',y='Predicted',data=results.head(50)) #blue is predicted





Tn [1	
TII I	1.5	
_	-	