```
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.head()
Out[3]:
            ID model engine_power age_in_days
                                                 km previous_owners
                                                                                  lon price
                                                                          lat
            1 lounge
                                          882
                                               25000
                                                                                      8900
                               51
                                                                 1 44.907242
                                                                              8.611560
                                         1186
                                               32500
                                                                 1 45.666359 12.241890
                               51
                                                                                      8800
                  pop
                                                                 1 45.503300 11.417840
                                              142228
             3
                               74
                                         4658
                                                                                      4200
                 sport
               lounge
                                              160000
                                                                 1 40.633171 17.634609
                               51
                                         2739
                                                                                      6000
                               73
                                         3074 106880
             5
                  pop
                                                                 1 41.903221 12.495650 5700
In [4]: datal=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	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	рор	51	1766	54276	1	40.323410	17.568270	7900

1389 rows × 9 columns

In [6]: data.describe()

Out[6]:

	lon	lat	previous_owners	km	age_in_days	engine_power	ID	
3.000000	1538.000000	1538.000000	1538.000000	1538.000000	1538.000000	1538.000000	1538.000000	count
6.003901	11.563428	43.541361	1.123537	53396.011704	1650.980494	51.904421	769.500000	mean
9.958641	2.328190	2.133518	0.416423	40046.830723	1289.522278	3.988023	444.126671	std
0.000000	7.245400	36.855839	1.000000	1232.000000	366.000000	51.000000	1.000000	min
2.500000	9.505090	41.802990	1.000000	20006.250000	670.000000	51.000000	385.250000	25%
0.000000	11.869260	44.394096	1.000000	39031.000000	1035.000000	51.000000	769.500000	50%
0.000000	12.769040	45.467960	1.000000	79667.750000	2616.000000	51.000000	1153.750000	75%
0.000000	18.365520	46.795612	4.000000	235000.000000	4658.000000	77.000000	1538.000000	max
9.95864 0.00000 2.50000 0.00000	2.328190 7.245400 9.505090 11.869260 12.769040	2.133518 36.855839 41.802990 44.394096 45.467960	0.416423 1.000000 1.000000 1.000000 1.000000	40046.830723 1232.000000 20006.250000 39031.000000 79667.750000	1289.522278 366.000000 670.000000 1035.000000 2616.000000	3.988023 51.000000 51.000000 51.000000	444.126671 1.000000 385.250000 769.500000 1153.750000	std min 25% 50% 75%

In [7]: | data=pd.get_dummies(data)

In [8]: data

Out[8]:

	ID	engine_power	age_in_days	km	previous_owners	lat	lon	price	model_lounge	model_pop	model_sport
0	1	51	882	25000	1	44.907242	8.611560	8900	1	0	0
1	2	51	1186	32500	1	45.666359	12.241890	8800	0	1	0
2	3	74	4658	142228	1	45.503300	11.417840	4200	0	0	1
3	4	51	2739	160000	1	40.633171	17.634609	6000	1	0	0
4	5	73	3074	106880	1	41.903221	12.495650	5700	0	1	0
1533	1534	51	3712	115280	1	45.069679	7.704920	5200	0	0	1
1534	1535	74	3835	112000	1	45.845692	8.666870	4600	1	0	0
1535	1536	51	2223	60457	1	45.481541	9.413480	7500	0	1	0
1536	1537	51	2557	80750	1	45.000702	7.682270	5990	1	0	0
1537	1538	51	1766	54276	1	40.323410	17.568270	7900	0	1	0

1538 rows × 11 columns

In [10]: data1

Out[10]:

	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 [11]: data.shape
Out[11]: (1538, 11)
In [12]: y=datal['price']
x=datal.drop('price',axis=1)
```

```
In [13]: y
Out[13]: 0
                 8900
                 8800
                 4200
         2
                 6000
         3
                 5700
         4
                 5200
         1533
         1534
                 4600
         1535
                 7500
         1536
                 5990
         1537
                 7900
         Name: price, Length: 1538, dtype: int64
```

In [14]: x

Out[14]:

	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

1538 rows × 7 columns

```
In [15]: data.info
Out[15]: <bound method DataFrame.info of</pre>
                                                    ID engine power age in days
                                                                                         km previous owners
                                                                                                                     lat
                                             882
                                                    25000
          0
                   1
                                 51
                                                                          1 44.907242
                   2
          1
                                 51
                                            1186
                                                    32500
                                                                            45.666359
          2
                   3
                                            4658
                                                   142228
                                                                            45.503300
                                 74
          3
                   4
                                 51
                                            2739
                                                   160000
                                                                             40.633171
          4
                   5
                                 73
                                            3074
                                                   106880
                                                                             41.903221
                                . . .
         1533
                1534
                                 51
                                            3712
                                                   115280
                                                                             45.069679
         1534
                1535
                                            3835
                                                   112000
                                                                             45.845692
                                 74
         1535
               1536
                                            2223
                                                    60457
                                 51
                                                                             45.481541
         1536
               1537
                                 51
                                            2557
                                                    80750
                                                                            45.000702
         1537 1538
                                 51
                                            1766
                                                    54276
                                                                          1 40.323410
                                                             model sport
                                   model lounge
                           price
                                                  model pop
                 8.611560
                             8900
          0
          1
                12.241890
                             8800
          2
                11.417840
                             4200
                                                          0
          3
                17.634609
                             6000
          4
                12.495650
                             5700
                              . . .
          . . .
                 7.704920
                             5200
         1533
                                               0
                                                          0
          1534
                 8.666870
                             4600
                                                          0
         1535
                 9.413480
                             7500
                                                          1
         1536
                 7.682270
                             5990
                                                          0
         1537
                17.568270
                             7900
                                               0
          [1538 rows x 11 columns]>
In [16]: 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 [17]: x_test.head()

Out[17]:

	engine_power	age_in_days	km	previous_owners	model_lounge	model_pop	model_sport
481	51	3197	120000	2	0	1	0
76	62	2101	103000	1	0	1	0
1502	51	670	32473	1	1	0	0
669	51	913	29000	1	1	0	0
1409	51	762	18800	1	1	0	0

```
In [18]: y_test.head()
Out[18]: 481
                 7900
         76
                 7900
         1502
                 9400
         669
                 8500
                 9700
         1409
         Name: price, dtype: int64
In [19]: y_train.head()
Out[19]: 527
                9990
         129
                9500
         602
                7590
                8750
         331
         323
                9100
         Name: price, dtype: int64
```

```
In [20]: y test.head()
Out[20]: 481
                 7900
         76
                 7900
         1502
                 9400
         669
                 8500
                 9700
         1409
         Name: price, dtype: int64
In [21]: from sklearn.linear_model import LinearRegression
         reg=LinearRegression() #creating object of LinearRegression
         reg.fit(x_train,y_train) #training are fitting LR object using training data
Out[21]:
          ▼ LinearRegression
          LinearRegression()
```

```
In [22]: ypred=reg.predict(x_test)
ypred
```

```
8840.08397206,
                 9916.27565791. 10287.45603992.
                                                  9964.3213269 .
8403.51255128,
                 9345.81907605,
                                  8521.46225147.
                                                  9743.68712672.
 9791.34520178,
                 9779.16293972,
                                  6753.27416058,
                                                  7354.16762745,
 8760.24542762,
                 9923.66596418,
                                  9812.92276721, 10466.90125415,
                                                  8866.7826029 ,
 8163.46726237,
                 6659.46839415,
                                  9987.65677522,
9952.37340054, 10187.72427693, 10231.39378767, 10091.11325493,
 9365.98570732, 10009.10088406,
                                  9141.00566394, 10099.11667176,
 7803.77049829,
                 6009.84398185,
                                  8800.33824151, 10237.60733785,
 5609.98366311, 10097.61555355,
                                  9684.99946572,
                                                  7644.67379732,
                 7371.5492091 ,
9276.37891542,
                                10287.98873148, 10067.26428381,
10552.64805598,
                 9966.72383894, 10068.46126756,
                                                  6232.53552963,
10584.55044373,
                 9965.98687522, 10529.44404458,
                                                  9602.67646085,
 9665.77720284,
                 6186.06948587,
                                  8073.87436253, 10345.58323918,
                 7361.62678204, 10058.57116223,
 6344.74803956,
                                                  6792.219309
 7897.72464823,
                 5261.45936067,
                                  4540.24137423,
                                                  8709.36468047,
                 7406.73353952,
 6882.0117409 ,
                                  6795.61189392,
                                                  7047.27998963,
                 8856.93910595,
                                  9378.02074127, 10389.561154
 9945.33400083,
10092.46332921, 10381.52000388,
                                                  5996.3331428
                                  9723.92466625,
 9786.14866981,
                 7708.49649098,
                                  5583.48163469,
                                                  4932.92788329,
```

```
In [23]: 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[23]:    GridSearchCV
    **estimator: Ridge**
    **Ridge**
    **Ridge**
```

```
In [24]: ridge_regressor.best_params_
Out[24]: {'alpha': 30}
In [25]: ridge=Ridge(alpha=30)
    ridge.fit(x_train,y_train)
    y_pred_ridge=ridge.predict(x_test)
In [26]: ypred=ridge_regressor.predict(x_test)
```

```
In [27]: ypred
                  7880.06692968.
                                  5421.58854259.
                                                  9908.298/2913. 1038/.14911484.
                 9677.04064086,
                                  8839.64921963,
                                                  7758.04496364,
                                                                  4272.30358351,
                 9879.24583245, 10338.32300002,
                                                  5727.64824413, 10176.30365568,
                 9496.76688181.
                                 7988.08471853.
                                                                  9891.06127373.
                                                  5547.3732031 .
                10434.86357188,
                                 6372.31423723,
                                                  9587.41260499,
                                                                  9566.83486068,
                10319.17531038,
                                 9522.2341334 ,
                                                  9810.96209247,
                                                                  9614.20063768,
                 6793.94641746,
                                 7934.18123669, 10386.9650737, 10348.55568749,
                 7374.24832772,
                                 9962.8313526 , 10427.75958382 , 10537.05691733 ,
                10307.86764216, 10057.84775154,
                                                  9522.79576023,
                                                                  7736.32759234,
                 9304.38969384, 10047.72953114, 10001.16290595,
                                                                  9982.03783683,
                 9356.45889265,
                                  9557.79360856,
                                                  9751.29744779,
                                                                  9816.27815842,
                 8772.11589722,
                                 6246.5681686 ,
                                                  6297.83377181,
                                                                  8210.43368425,
                 8609.44775082,
                                  6555.65279459,
                                                  6842.30381123,
                                                                  5501.4318499 ,
                 8113.64452407,
                                 9844.22280324,
                                                  7768.73012027,
                                                                  9871.53450863,
                                                  9831.08379287, 10040.2716485,
                10142.9208104 ,
                                  5807.87769524,
                                                                  3821.65817325,
                 8019.70650821,
                                  4516.41557946, 10577.27619954,
                 9948.97058812, 10508.26237361,
                                                  5721.78144051,
                                                                  5476.739495
                                 6788.56652042,
                10392.79176695,
                                                  8948.54811289, 10424.84703341,
                 9450.82424662,
                                 9972.71312863,
                                                  8547.62184364,
                                                                  7954.86597122,
                10396.93269263,
                                  5351.3569159 ,
                                                  9895.97517221, 10199.69230161,
In [28]: 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[28]:
                 GridSearchCV
           ▶ estimator: ElasticNet
                ▶ ElasticNet
```

```
In [29]: elastic regressor.best params
Out[29]: {'alpha': 0.01}
In [30]: elastic=ElasticNet(alpha=30)
         elastic.fit(x train,y train)
         y pred elastic=elastic.predict(x test)
In [31]: from sklearn.metrics import mean squared error
         mean squared error(ypred,y test)
Out[31]: 579521.7970897449
In [32]: from sklearn.metrics import mean squared error
         Ridge Error=mean squared error(y pred ridge, y test)
         Ridge Error
Out[32]: 579521.7970897449
In [33]: from sklearn.metrics import mean squared error
         Elastic Error=mean squared error(y pred elastic,y test)
         Elastic Error
Out[33]: 580334.1755711779
In [34]: from sklearn.metrics import r2 score
         r2 score(y test,ypred) #ytest=actual price,ypred=predicted price
Out[34]: 0.8421969385523054
In [35]: from sklearn.metrics import r2 score
         r2 score(y test,y pred ridge) #ytest=actual price,ypred=predicted price
Out[35]: 0.8421969385523054
```