In [164]:

data=data.drop(['lat','lon','ID',],axis=1)

```
In [161]: import pandas as pd
In [162]: data=pd.read_csv("fiat500 (1).csv")
In [163]: data
Out[163]:
                        model engine_power age_in_days
                                                             km previous_owners
                                                                                       lat
                                                                                                 lon price
                                                     882
                                                          25000
                0
                                         51
                                                                              1 44.907242
                                                                                            8.611560
                                                                                                      8900
                      1 lounge
                1
                      2
                           pop
                                         51
                                                    1186
                                                          32500
                                                                              1 45.666359 12.241890
                                                                                                      8800
                2
                          sport
                                         74
                                                    4658
                                                         142228
                                                                              1 45.503300 11.417840
                                                                                                      4200
                3
                                         51
                                                         160000
                                                                               1 40.633171 17.634609
                                                                                                      6000
                      4 lounge
                                                    2739
                                                         106880
                                                                              1 41.903221 12.495650
                                         73
                                                                                                      5700
                                                    3074
                           pop
             1533 1534
                                                    3712 115280
                                                                              1 45.069679
                                                                                            7.704920
                                                                                                      5200
                          sport
                                         51
                                                    3835 112000
             1534
                  1535
                        lounge
                                         74
                                                                              1 45.845692
                                                                                            8.666870
                                                                                                      4600
             1535 1536
                                                                                            9.413480
                                         51
                                                    2223
                                                          60457
                                                                               1 45.481541
                                                                                                      7500
                           pop
                                                                                            7.682270
             1536 1537
                                                    2557
                                                          80750
                                                                              1 45.000702
                                                                                                      5990
                        lounge
                                         51
             1537 1538
                                                          54276
                                                                              1 40.323410 17.568270
                                         51
                                                    1766
                                                                                                     7900
                           pop
            1538 rows × 9 columns
```

In [165]: data

Out[165]:

	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 [166]: data=pd.get_dummies(data)
In [167]: data.shape
    #data['model'] = data['model'].map({'lounge':1,'pop':2,'sport':3})
Out[167]: (1538, 8)
```

In [168]: data

Out[168]:

	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 [169]: y=data['price']
x=data.drop('price',axis=1)
```

```
In [170]: y
Out[170]: 0
                  8900
                  8800
                  4200
          2
          3
                  6000
                  5700
          1533
                  5200
          1534
                  4600
          1535
                  7500
          1536
                  5990
          1537
                  7900
          Name: price, Length: 1538, dtype: int64
```

In [171]: 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 [172]: X_test.head(5)

Out[172]:

	engine_power	age_in_days	km	previous_owners	model_lounge	model_pop	model_sport
48	1 51	3197	120000	2	0	1	0
7	6 62	2101	103000	1	0	1	0
150	2 51	670	32473	1	1	0	0
66	9 51	913	29000	1	1	0	0
140	9 51	762	18800	1	1	0	0

In [173]: X_train.shape

Out[173]: (1030, 7)

```
In [174]: y train
Out[174]: 527
                   9990
          129
                   9500
          602
                   7590
          331
                   8750
          323
                   9100
                  10990
          1130
          1294
                   9800
          860
                   5500
          1459
                   9990
          1126
                   8900
          Name: price, Length: 1030, dtype: int64
In [175]: from sklearn.linear_model import LinearRegression
          reg = LinearRegression()
                                     #creating object of linearregression
          reg.fit(X train,y train)
                                     #training and fitting LR object using training data
Out[175]:
           ▼ LinearRegression
          LinearRegression()
In [176]: ypred=reg.predict(X_test)
```

```
In [177]:
          ypred
                 10352.85155564,
                                  8045.2158800/, 10440.80004/58,
                                                                  3/30.20118808,
                 10348.63930496, 10435.96627494, 6167.80169017, 10390.11317804,
                  6527.69471073.
                                  9116.4755691 . 10484.52829
                                                                  9335.69889855.
                  6709.57413543.
                                  3390.72353093. 10106.33753331.
                                                                  9792.46732008.
                  6239.49568346,
                                  4996.26346266,
                                                  9044.38667681,
                                                                  9868.09959448,
                                  5698.5954821 , 10086.86206874,
                  5484.13199252,
                                                                  8115.81693479,
                 10392.37800936.
                                  6835.6573351 .
                                                  6657.61744836.
                                                                  5738.50576764.
                  8896.80120764,
                                  9952.37340054, 10390.28377419,
                                                                  9419.10788866,
                  9082.56591129, 10122.82465116, 10410.00504522, 10151.77663915,
                  9714.85367238.
                                  9291.92963633. 10346.99073888.
                                                                  5384.22311343.
                  9772.85146492,
                                  6069.77107828,
                                                  9023.26394782, 10220.56195956,
                  9238.89392583,
                                  9931.47195375,
                                                  8321.42715662,
                                                                  8377.80491069,
                  7528.53327408, 10552.64805598, 10465.02437243, 10110.68940664,
                 10238.17869436,
                                  6841.77264488,
                                                  9625.64505547, 10412.59988875,
                  9653.06224923, 7948.63618724,
                                                  9704.82523573,
                                                                  7971.05970955,
                 10399.51752022,
                                  9176.43567301,
                                                  5803.03205787,
                                                                  6698.19524313,
                                                                  9789.65062843,
                  8257.83550573, 10452.95284574,
                                                  9948.66454584.
                 10582.50828537, 7568.91955482,
                                                  6804.97705225,
                                                                  8065.01292384,
                 10310.29143419,
                                  8836.34894739,
                                                  8390.05091229,
                                                                  9582.13932508,
                  0745 24704001 10045 45021207 10204 00072015
                                                                  71/5 152152/0
In [178]: from sklearn.metrics import r2 score
          r2 score(v test, vpred)
Out[178]: 0.8415526986865394
In [179]: from sklearn.metrics import mean squared error
          mean squared error(ypred,y test)
Out[179]: 581887.727391353
In [180]: #from sklearn.metrics import accuracy score
          #accuracy score(y test,ypred)
```

In [181]: Results= pd.DataFrame(columns=['Price','Predicted']) Results['Price']=y_test Results['Predicted']=ypred Results=Results.reset_index() Results['Id']=Results.index Results.head(15)

Out[181]:

	index	Price	Predicted	ld
0	481	7900	5867.650338	0
1	76	7900	7133.701423	1
2	1502	9400	9866.357762	2
3	669	8500	9723.288745	3
4	1409	9700	10039.591012	4
5	1414	9900	9654.075826	5
6	1089	9900	9673.145630	6
7	1507	9950	10118.707281	7
8	970	10700	9903.859527	8
9	1198	8999	9351.558284	9
10	1088	9890	10434.349636	10
11	576	7990	7732.262557	11
12	965	7380	7698.672401	12
13	1488	6800	6565.952404	13
14	1432	8900	9662.901035	14

```
In [182]: Results= pd.DataFrame(columns=['Price', 'Predicted'])
    Results['Price']=y_test
    Results['Predicted']=ypred
    Results=Results.reset_index()
    Results['Id']=Results.index
    Results.head(25)
```

Out[182]:

	index	Price	Predicted	ld
0	481	7900	5867.650338	0
1	76	7900	7133.701423	1
2	1502	9400	9866.357762	2
3	669	8500	9723.288745	3
4	1409	9700	10039.591012	4
5	1414	9900	9654.075826	5
6	1089	9900	9673.145630	6
7	1507	9950	10118.707281	7
8	970	10700	9903.859527	8
9	1198	8999	9351.558284	9
10	1088	9890	10434.349636	10
11	576	7990	7732.262557	11
12	965	7380	7698.672401	12
13	1488	6800	6565.952404	13
14	1432	8900	9662.901035	14
15	380	10500	10373.203443	15
16	754	10690	9599.948445	16
17	30	6990	7699.344004	17
18	49	4300	4941.330180	18
19	240	10500	10455.271948	19
20	344	9980	10370.515557	20

	index	Price	Predicted	ld
21	354	10500	10391.604244	21
22	124	7500	7529.066225	22
23	383	9600	9952.373401	23
24	1389	5500	7006.138457	24

In [183]: data.describe()

Out[183]:

	engine_power	age_in_days	km	previous_owners	price	model_lounge	model_pop	model_sport
count	1538.000000	1538.000000	1538.000000	1538.000000	1538.000000	1538.000000	1538.000000	1538.000000
mean	51.904421	1650.980494	53396.011704	1.123537	8576.003901	0.711313	0.232770	0.055917
std	3.988023	1289.522278	40046.830723	0.416423	1939.958641	0.453299	0.422734	0.229836
min	51.000000	366.000000	1232.000000	1.000000	2500.000000	0.000000	0.000000	0.000000
25%	51.000000	670.000000	20006.250000	1.000000	7122.500000	0.000000	0.000000	0.000000
50%	51.000000	1035.000000	39031.000000	1.000000	9000.000000	1.000000	0.000000	0.000000
75%	51.000000	2616.000000	79667.750000	1.000000	10000.000000	1.000000	0.000000	0.000000
max	77.000000	4658.000000	235000.000000	4.000000	11100.000000	1.000000	1.000000	1.000000

In [184]: # ridge regression

```
In [185]: 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)
          /home/placement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
          Ill-conditioned matrix (rcond=5.56109e-26): result may not be accurate.
            return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
          /home/placement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
          Ill-conditioned matrix (rcond=7.70876e-26): result may not be accurate.
            return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
          /home/placement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
          Ill-conditioned matrix (rcond=6.91585e-23): result may not be accurate.
            return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
          /home/placement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
          Ill-conditioned matrix (rcond=7.08003e-23): result may not be accurate.
            return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
          /home/placement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
          Ill-conditioned matrix (rcond=7.01022e-23): result may not be accurate.
            return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
          /home/placement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
          Ill-conditioned matrix (rcond=7.57959e-23): result may not be accurate.
            return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
          /home/placement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
          Ill-conditioned matrix (rcond=7.24161e-23): result may not be accurate.
            return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
          /home/placement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
          Ill-conditioned matrix (rcond=6.92759e-21): result may not be accurate.
            return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
          /home/placement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
          Ill-conditioned matrix (rcond=7.09091e-21): result may not be accurate.
            return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
          /home/placement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
```

In [187]: ridge=Ridge(alpha=30)

ridge.fit(X train,y train)

y pred ridge=ridge.predict(X test)

```
Ill-conditioned matrix (rcond=7.02112e-21): result may not be accurate.
            return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
          /home/placement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
          Ill-conditioned matrix (rcond=7.57414e-21): result may not be accurate.
            return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
          /home/placement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
          Ill-conditioned matrix (rcond=7.23284e-21): result may not be accurate.
            return linalq.solve(A, Xy, assume a="pos", overwrite a=True).T
          /home/placement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
          Ill-conditioned matrix (rcond=6.9277e-17): result may not be accurate.
            return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
          /home/placement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
          Ill-conditioned matrix (rcond=7.09099e-17): result may not be accurate.
            return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
          /home/placement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
          Ill-conditioned matrix (rcond=7.02123e-17): result may not be accurate.
            return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
          /home/placement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
          Ill-conditioned matrix (rcond=7.57407e-17): result may not be accurate.
            return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
          /home/placement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
          Ill-conditioned matrix (rcond=7.23274e-17): result may not be accurate.
            return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
Out[185]:
             GridSearchCV
           ▶ estimator: Ridge
                 ▶ Ridge
In [186]: ridge_regressor.best_params_
Out[186]: {'alpha': 30}
```

In [188]: Ridge_Error=mean_squared_error(y_pred_ridge,y_test)
Ridge_Error

Out[188]: 579521.7970897449

In [189]: from sklearn.metrics import r2_score
 r2_score(y_test,ypred)

Out[189]: 0.8415526986865394

```
In [190]: 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[190]:

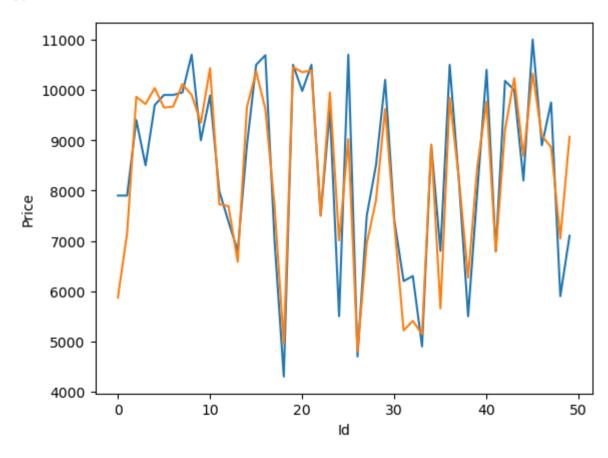
	index	Price	Predicted	ld
0	481	7900	5869.741155	0
1	76	7900	7149.563327	1
2	1502	9400	9862.785355	2
3	669	8500	9719.283532	3
4	1409	9700	10035.895686	4
5	1414	9900	9650.311090	5
6	1089	9900	9669.183317	6
7	1507	9950	10115.128380	7
8	970	10700	9900.241944	8
9	1198	8999	9347.080772	9
10	1088	9890	10431.237961	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 [192]: 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[192]: []



```
In [ ]:

In [ ]:
```

In []:	
In []:	
In []:	
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In []:	