```
In [176]:
          import pandas as pd
          import warnings
          warnings.filterwarnings('ignore')
          data=pd.read csv("/home/placement/Downloads/fiat500.csv")
          print(data)
                   ID
                        model
                                engine power
                                               age in days
                                                                     previous owners \
          0
                    1
                       lounge
                                          51
                                                       882
                                                             25000
                                                                                    1
          1
                    2
                                           51
                                                      1186
                                                             32500
                                                                                    1
                          pop
                    3
                        sport
                                           74
                                                      4658
                                                            142228
           3
                       lounge
                                           51
                                                      2739
                                                            160000
                    4
                                                                                    1
           4
                    5
                                           73
                                                      3074
                                                            106880
                                                                                    1
                          pop
                          . . .
                                                       . . .
                                                                . . .
          1533
                                                            115280
                 1534
                                          51
                                                      3712
                        sport
                                                                                    1
          1534
                 1535
                                           74
                                                      3835
                                                            112000
                       lounge
          1535 1536
                                           51
                                                      2223
                                                             60457
                                                                                    1
                          pop
          1536
                1537
                                           51
                                                      2557
                                                             80750
                                                                                    1
                       lounge
          1537 1538
                          pop
                                           51
                                                      1766
                                                              54276
                                                                                    1
                       lat
                                   lon
                                        price
                 44.907242
                              8.611560
                                         8900
          0
           1
                 45.666359
                            12.241890
                                         8800
           2
                 45.503300 11.417840
                                         4200
           3
                 40.633171 17.634609
                                         6000
           4
                 41.903221
                            12.495650
                                         5700
                        . . .
                                   . . .
                                           . . .
           . . .
          1533
                 45.069679
                              7.704920
                                          5200
          1534
                45.845692
                              8.666870
                                         4600
          1535
                 45.481541
                              9.413480
                                         7500
          1536
                 45.000702
                              7.682270
                                         5990
          1537
                 40.323410
                            17.568270
                                         7900
```

[1538 rows x 9 columns]

In [177]: data.head(10)

Out[177]:

	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	pop	73	3074	106880	1	41.903221	12.495650	5700
5	6	рор	74	3623	70225	1	45.000702	7.682270	7900
6	7	lounge	51	731	11600	1	44.907242	8.611560	10750
7	8	lounge	51	1521	49076	1	41.903221	12.495650	9190
8	9	sport	73	4049	76000	1	45.548000	11.549470	5600
9	10	sport	51	3653	89000	1	45.438301	10.991700	6000

In [178]: data.tail()

Out[178]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	lon	price
1533	1534	sport	51	3712	115280	1	45.069679	7.70492	5200
1534	1535	lounge	74	3835	112000	1	45.845692	8.66687	4600
1535	1536	pop	51	2223	60457	1	45.481541	9.41348	7500
1536	1537	lounge	51	2557	80750	1	45.000702	7.68227	5990
1537	1538	pop	51	1766	54276	1	40.323410	17.56827	7900

In [179]: data.shape

Out[179]: (1538, 9)

```
data.columns
In [180]:
Out[180]: Index(['ID', 'model', 'engine power', 'age in days', 'km', 'previous owners',
                     'lat', 'lon', 'price'],
                    dtype='object')
In [181]:
            data.describe()
Out[181]:
                             ID engine power
                                              age in days
                                                                         previous owners
                                                                                                  lat
                                                                                                             lon
                                                                                                                         price
              count 1538.000000
                                                                             1538.000000 1538.000000
                                  1538.000000
                                              1538.000000
                                                             1538.000000
                                                                                                     1538.000000
                                                                                                                   1538.000000
              mean
                     769.500000
                                    51.904421
                                              1650.980494
                                                            53396.011704
                                                                                1.123537
                                                                                            43.541361
                                                                                                        11.563428
                                                                                                                   8576.003901
                std
                     444.126671
                                     3.988023
                                               1289.522278
                                                            40046.830723
                                                                                0.416423
                                                                                            2.133518
                                                                                                         2.328190
                                                                                                                   1939.958641
                       1.000000
                                                                                                         7.245400
                                    51.000000
                                                366.000000
                                                             1232.000000
                                                                                1.000000
                                                                                            36.855839
                                                                                                                   2500.000000
               min
               25%
                     385.250000
                                    51.000000
                                               670.000000
                                                            20006.250000
                                                                                1.000000
                                                                                            41.802990
                                                                                                         9.505090
                                                                                                                   7122.500000
               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.isna().sum()
In [182]:
Out[182]: ID
                                    0
            model
                                    0
            engine_power
            age_in_days
             km
            previous_owners
                                    0
             lat
                                    0
             lon
            price
            dtype: int64
```

### remove unwanted columns

```
In [183]: data1=data.drop(columns=['ID','lon','lat'])
In [184]: data1
```

Out[184]:

	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

# convert the strings into numbers on column using get\_dummies()

```
In [185]: datal=pd.get_dummies(datal)
```

In [186]: data1

Out[186]:

	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 [187]: data2=data1.loc[(data1.model_lounge==1)]
```

In [188]: data2

Out[188]:

	engine_power	age_in_days	km	previous_owners	price	model_lounge	model_pop	model_sport
0	51	882	25000	1	8900	1	0	0
3	51	2739	160000	1	6000	1	0	0
6	51	731	11600	1	10750	1	0	0
7	51	1521	49076	1	9190	1	0	0
11	51	366	17500	1	10990	1	0	0
1528	51	2861	126000	1	5500	1	0	0
1529	51	731	22551	1	9900	1	0	0
1530	51	670	29000	1	10800	1	0	0
1534	74	3835	112000	1	4600	1	0	0
1536	51	2557	80750	1	5990	1	0	0

1094 rows × 8 columns

```
In [189]: y=data2['price']
x=data2.drop(['price','model_pop','model_sport'],axis=1)
```

In [190]: x

Out[190]:

	engine_power	age_in_days	km	previous_owners	model_lounge
0	51	882	25000	1	1
3	51	2739	160000	1	1
6	51	731	11600	1	1
7	51	1521	49076	1	1
11	51	366	17500	1	1
1528	51	2861	126000	1	1
1529	51	731	22551	1	1
1530	51	670	29000	1	1
1534	74	3835	112000	1	1
1536	51	2557	80750	1	1

1094 rows × 5 columns

```
In [191]: y
Out[191]: 0
                    8900
                    6000
                  10750
          6
                   9190
                  10990
          11
                   . . .
          1528
                   5500
          1529
                    9900
          1530
                  10800
          1534
                    4600
          1536
                    5990
          Name: price, Length: 1094, dtype: int64
```

# splitting the data into training set and testing set

In [192]: 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 [193]: x\_train

Out[193]:

	engine_power	age_in_days	km	previous_owners	model_lounge
441	51	762	36448	1	1
701	51	701	27100	1	1
695	51	3197	51083	1	1
1415	51	670	33000	1	1
404	51	456	14000	1	1
459	51	397	15628	1	1
654	51	3227	95554	1	1
189	51	1431	81900	1	1
1455	51	701	33942	1	1
1218	51	882	25000	1	1

732 rows × 5 columns

```
In [194]: y_train
Out[194]: 441
                   8980
          701
                  10300
          695
                   5880
          1415
                  10490
          404
                   9499
                   . . .
          459
                  10850
          654
                   5900
          189
                  10000
          1455
                   9400
          1218
                   8900
          Name: price, Length: 732, dtype: int64
```

In [195]: x\_test

#### Out[195]:

	engine_power	age_in_days	km	previous_owners	model_lounge
676	51	762	18609	1	1
215	51	701	25000	1	1
146	51	4018	152900	1	1
1319	51	731	20025	1	1
1041	51	640	38231	1	1
757	51	4018	102841	1	1
167	51	397	15341	1	1
156	51	1858	35304	1	1
1145	51	456	14970	1	1
1393	51	609	32665	2	1

362 rows × 5 columns

```
In [196]: y test
Out[196]: 676
                   10250
          215
                    9790
          146
                    5500
          1319
                    9900
          1041
                    8900
          757
                    6000
                   10950
          167
          156
                    8000
          1145
                   10700
          1393
                    9400
          Name: price, Length: 362, dtype: int64
```

### **Ridge Regression**

```
In [199]: ridge=Ridge(alpha=30)
    ridge.fit(x_train,y_train)
    y_pred=ridge.predict(x_test)

In [200]: Ridge_Error=mean_squared_error(y_pred,y_test)
Ridge_Error

Out[200]: 519771.8129989745

In [201]: from sklearn.metrics import r2_score #to know the efficiency of the predicted price
    r2_score(y_test,y_pred)

Out[201]: 0.8373030813683994

In [202]: results=pd.DataFrame(columns=['Actual','Predicted'])
    results['Actual']=y_test
    results['Predicted']=y_pred
```

```
In [203]: results
```

Out[203]:

	Actual	Predicted
676	10250	10045.347779
215	9790	9989.171535
146	5500	4769.099603
1319	9900	10048.683238
1041	8900	9813.944798
757	6000	5640.378648
167	10950	10431.681162
156	8000	8765.506865
1145	10700	10384.884273
1393	9400	9929.721685

362 rows × 2 columns

```
In [204]: results["Difference"]=results.apply(lambda x:x.Actual-x.Predicted,axis=1)
```

```
In [210]: results["id"]=results.index
```

In [211]: results

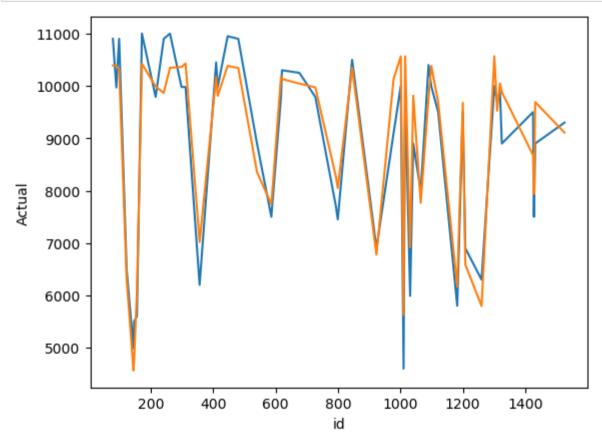
Out[211]:

	Actual	Predicted	Difference	id
676	10250	10045.347779	204.652221	676
215	9790	9989.171535	-199.171535	215
146	5500	4769.099603	730.900397	146
1319	9900	10048.683238	-148.683238	1319
1041	8900	9813.944798	-913.944798	1041
757	6000	5640.378648	359.621352	757
167	10950	10431.681162	518.318838	167
156	8000	8765.506865	-765.506865	156
1145	10700	10384.884273	315.115727	1145
1393	9400	9929.721685	-529.721685	1393

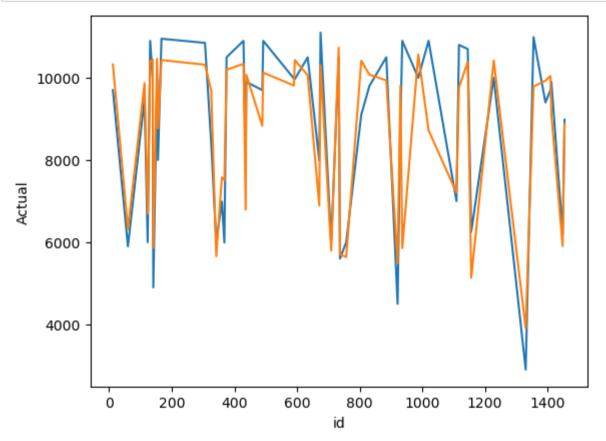
362 rows × 4 columns

# Plot the data

```
In [226]: import seaborn as sns
import matplotlib.pyplot as plt
sns.lineplot(x='id',y='Actual',data=results.head(50))
sns.lineplot(x='id',y='Predicted',data=results.head(50))
plt.show()
```



```
In [215]: sns.lineplot(x='id',y='Actual',data=results.tail(50))
sns.lineplot(x='id',y='Predicted',data=results.tail(50))
plt.show()
```



In [ ]: