```
In [1]:
        import pandas as pd
        import warnings
        warnings.filterwarnings('ignore')
        data=pd.read csv("/home/placement/Downloads/fiat500.csv") #reading datafile
        print(data)
                 ID
                      model
                              engine power
                                             age in days
                                                               km
                                                                   previous owners \
                                                            25000
                     lounge
                                         51
                                                     882
        0
                  1
                                                                                  1
         1
                  2
                        pop
                                         51
                                                    1186
                                                            32500
                                                                                  1
         2
                  3
                      sport
                                         74
                                                    4658
                                                          142228
                                                                                  1
                                                          160000
         3
                     lounge
                                         51
                                                    2739
                                                                                  1
         4
                  5
                                         73
                                                    3074
                                                          106880
                        pop
                         . . .
                                                     . . .
                . . .
                                        . . .
         . . .
         1533
               1534
                                         51
                                                    3712
                                                          115280
                                                                                  1
                       sport
        1534
              1535
                                         74
                                                    3835
                                                          112000
                                                                                  1
                     lounge
        1535
              1536
                                         51
                                                    2223
                                                           60457
                                                                                  1
                         pop
        1536
               1537
                                         51
                                                    2557
                                                            80750
                     lounge
        1537 1538
                                         51
                                                    1766
                                                            54276
                                                                                  1
                        pop
                     lat
                                 lon
                                      price
               44.907242
                            8.611560
                                       8900
         0
         1
               45.666359
                          12.241890
                                       8800
         2
               45.503300
                          11.417840
                                        4200
               40.633171
                          17.634609
                                       6000
         4
               41.903221
                          12.495650
                                       5700
                                         . . .
                                 . . .
         . . .
               45.069679
                            7.704920
        1533
                                        5200
               45.845692
                            8.666870
        1534
                                        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 [2]: data.head(10)

Out[2]:		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
	5	6	pop	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 [5]: data.describe()

Out[5]:

	ID	engine_power	age_in_days	km	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
min	1.000000	51.000000	366.000000	1232.000000	1.000000	36.855839	7.245400	2500.000000
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

# **Removing unwanted columns**

```
In [6]: data1=data.drop(columns=["ID","lat","lon"])
```

In [7]: data1

Out[7]:

	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 [8]: data1=pd.get\_dummies(data1)

In	[9]	:	data1
	$\Gamma \sim 1$		aacar

Out[9]

l :		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 [10]: data1.shape
```

Out[10]: (1538, 8)

## remove the actual value from the dataframe

```
In [11]: y=data1['price']
x=data1.drop(columns='price')
```

In [12]: x

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v	u		L	_	_		

	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 [13]: y
```

```
Out[13]: 0
                 8900
                 8800
         2
                 4200
         3
                 6000
         4
                 5700
                  . . .
         1533
                 5200
         1534
                 4600
         1535
                 7500
         1536
                 5990
         1537
                 7900
```

Name: price, Length: 1538, dtype: int64

```
In [14]: #!pip install scikit-learn
```

## split the data into training set and testing set

In [15]: 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)# 66% and 33%

In [16]: x\_test

Out[16]:

	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
291	51	701	22000	1	1	0	0
596	51	3347	85500	1	0	1	0
1489	51	366	22148	1	0	1	0
1436	51	1797	61000	1	1	0	0
575	51	366	19112	1	1	0	0

508 rows × 7 columns

In [17]: x\_train

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·	u			_ /	- 1

	engine_power	age_in_days	km	previous_owners	model_lounge	model_pop	model_sport
527	51	425	13111	1	1	0	0
129	51	1127	21400	1	1	0	0
602	51	2039	57039	1	0	1	0
331	51	1155	40700	1	1	0	0
323	51	425	16783	1	1	0	0
1130	51	1127	24000	1	1	0	0
1294	51	852	30000	1	1	0	0
860	51	3409	118000	1	0	1	0
1459	51	762	16700	1	1	0	0
1126	51	701	39207	1	1	0	0

1030 rows × 7 columns

In [18]: | y\_test.head(5)

Out[18]: 481

481 7900 76 7900 1502 9400 669 8500 1409 9700

Name: price, dtype: int64

## LinearRegression

```
In [20]: from sklearn.linear_model import LinearRegression
    reg=LinearRegression()#creating object of LinearRegression
    reg.fit(x_train,y_train)#training and fitting

Out[20]: LinearRegression()
    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 nbviewer.org.

In [55]: y_pred_regression=reg.predict(x_test) #predict the price using x test data
```

```
In [56]: y pred regression
Out[56]: array([ 5867.6503378 ,
                                  7133.70142341.
                                                  9866.35776216.
                                                                  9723.28874535.
                                 9654.07582608.
                10039.59101162.
                                                  9673.14563045. 10118.70728123.
                 9903.85952664,
                                 9351.55828437, 10434.34963575, 7732.26255693,
                 7698.67240131,
                                 6565.95240435,
                                                  9662.90103518, 10373.20344286,
                                                  4941.33017994, 10455.2719478 ,
                 9599.94844451,
                                 7699.34400418.
                10370.51555682, 10391.60424404,
                                                  7529.06622456.
                                                                  9952.37340054,
                 7006.13845729,
                                 9000.1780961 ,
                                                  4798.36770637,
                                                                  6953.10376491,
                                                                  5229.18705519,
                 7810.39767825,
                                 9623.80497535,
                                                  7333.52158317,
                                                  8948.63632836,
                                                                  5666.62365159,
                 5398.21541073,
                                 5157.65652129,
                 9822.1231461 ,
                                 8258.46551788,
                                                  6279.2040404 ,
                                                                  8457.38443276,
                 9773.86444066,
                                 6767.04074749,
                                                  9182.99904787, 10210.05195479,
                 8694.90545226, 10328.43369248,
                                                  9069.05761443,
                                                                  8866.7826029 .
                 7058.39787506, 9073.33877162,
                                                  9412.68162121, 10293.69451263,
                10072.49011135,
                                 6748.5794244 ,
                                                  9785.95841801,
                                                                  9354.09969973,
                 9507.9444386 , 10443.01608254,
                                                  9795.31884316,
                                                                  7197.84932877,
                10108.31707235, 7009.6597206,
                                                  9853.90699412,
                                                                  7146.87414965,
                 6417.69133992,
                                 9996.97382441,
                                                  9781.18795953,
                                                                  8515.83255277,
                                                  7768.57829985,
                                                                  6832.86406122,
                 8456.30006203,
                                 6499.76668237,
                                                  7356.43463051.
                 8347.96113362. 10439.02404036.
                                                                  8562.56562053.
In [57]: from sklearn.metrics import r2 score #to know the efficiency bw the predicted price
         r2 score(y test,y pred regression)
Out[57]: 0.8415526986865394
In [58]: from sklearn.metrics import mean squared_error#calaculating mse
         mean squared error(y test,y pred regression)
Out[58]: 581887.727391353
In [59]: import math
         a=581887.727391353
         print(math.sqrt(a))
         762.8156575420782
```

```
In [60]: y test.head(10)
Out[60]: 481
                  7900
                  7900
         76
         1502
                  9400
         669
                  8500
         1409
                  9700
                  9900
         1414
         1089
                  9900
         1507
                  9950
         970
                 10700
         1198
                  8999
         Name: price, dtype: int64
In [61]: results=pd.DataFrame(columns=['Price', 'Predicted']) #create datafame for price and predicted
         results['Price']=y test
         results['Predicted']=y_pred_regression
         results=results.reset index()
                                        #remove the index as ID values
         results['id']=results.index
```

#### In [62]: results

Out[62]:

	index	Price	Predicted	id
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
•••				
503	291	10900	10032.665135	503
504	596	5699	6281.536277	504
505	1489	9500	9986.327508	505
506	1436	6990	8381.517020	506
507	575	10900	10371.142553	507

508 rows × 4 columns

In [63]: results["Difference"]=results.apply(lambda x:x.Price-x.Predicted,axis=1)#add the column for difference b/w t

In [64]:

results.head(10)

Out[64]:

	index	Price	Predicted	id	Difference
0	481	7900	5867.650338	0	2032.349662
1	76	7900	7133.701423	1	766.298577
2	1502	9400	9866.357762	2	-466.357762
3	669	8500	9723.288745	3	-1223.288745
4	1409	9700	10039.591012	4	-339.591012
5	1414	9900	9654.075826	5	245.924174
6	1089	9900	9673.145630	6	226.854370
7	1507	9950	10118.707281	7	-168.707281
8	970	10700	9903.859527	8	796.140473
9	1198	8999	9351.558284	9	-352.558284

In [65]: results

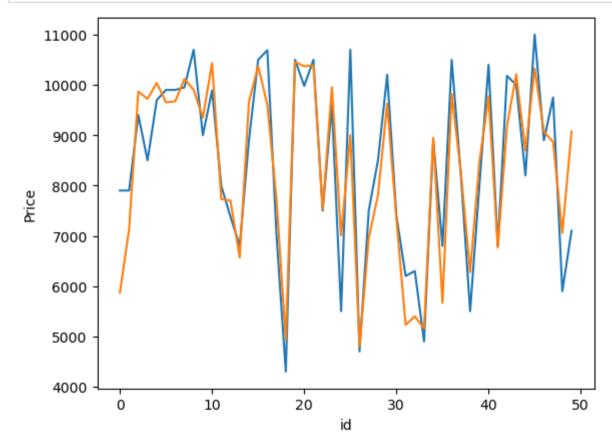
Out[65]:

_		index	Price	Predicted	id	Difference
	0	481	7900	5867.650338	0	2032.349662
	1	76	7900	7133.701423	1	766.298577
	2	1502	9400	9866.357762	2	-466.357762
	3	669	8500	9723.288745	3	-1223.288745
	4	1409	9700	10039.591012	4	-339.591012
	503	291	10900	10032.665135	503	867.334865
	504	596	5699	6281.536277	504	-582.536277
	505	1489	9500	9986.327508	505	-486.327508
	506	1436	6990	8381.517020	506	-1391.517020
	507	575	10900	10371.142553	507	528.857447

508 rows × 5 columns

# plot the data using seaborn and matplotlib libraries

```
In [33]: import seaborn as sns
import matplotlib.pyplot as plt
sns.lineplot(x='id',y='Price',data=results.head(50)) #actual color=blue
sns.lineplot(x='id',y='Predicted',data=results.head(50)) #predicted color=orange
plt.show()
```



## Ridge\_Regression

In [34]: **from** sklearn.model selection **import** GridSearchCV

```
from sklearn.linear model import Ridge
         alpha=[1e-15,1e-10,1e-4,1e-3,1e-2,15,10,20,30]
          ridge=Ridge()
                                                                 #creating an object for Ridge
         parameters={'alpha':alpha}
          ridge regressor=GridSearchCV(ridge,parameters)
          ridge regressor.fit(x train,y train)
                                                                 #training and fitting
Out[34]: GridSearchCV(estimator=Ridge(),
                       param grid={'alpha': [1e-15, 1e-10, 0.0001, 0.001, 0.01, 15, 10,
                                               20. 3011)
         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 [35]: ridge regressor.best params
Out[35]: {'alpha': 30}
In [66]: ridge=Ridge(alpha=30)
          ridge.fit(x train,y train)
         y pred ridge=ridge.predict(x test)
In [67]: | from sklearn.metrics import r2 score #to know the efficiency of the predicted price
         r2 score(y test,y pred ridge)
Out[67]: 0.8421969385523054
```

In [71]:

```
In [68]: from sklearn.metrics import mean squared error
          Ridge Error=mean squared error(y pred ridge,y test)
          Ridge Error
Out[68]: 579521.7970897449
In [69]: results=pd.DataFrame(columns=['Actual', 'Predicted']) #create the dataframe for actual and predicted values
          results['Actual']=v test
          results['Predicted']=y pred ridge
          results=results.reset index() #remove the index as ID values
          results['id']=results.index
In [70]: results
Out[70]:
                              Predicted
                                        id
               index Actual
             0
                 481
                      7900
                             5869.741155
                                         0
                  76
                      7900
                            7149.563327
                                         1
                1502
                      9400
                            9862.785355
                                         2
                 669
                      8500
                            9719.283532
                                         3
                1409
                      9700 10035.895686
           503
                 291
                     10900
                           10029.070743 503
           504
                 596
                      5699
                            6297.833772 504
           505
                1489
                      9500 10008.285472 505
           506
                1436
                      6990
                            8375.789449 506
           507
                     10900 10368.170257 507
          508 rows × 4 columns
```

results["Difference"]=results.apply(lambda x:x.Actual-x.Predicted,axis=1)#add the column for difference b/w

localhost:8888/notebooks/Data science/Analysis\_data/fiat\_data( LR%2CRR%2CEN models).ipynb

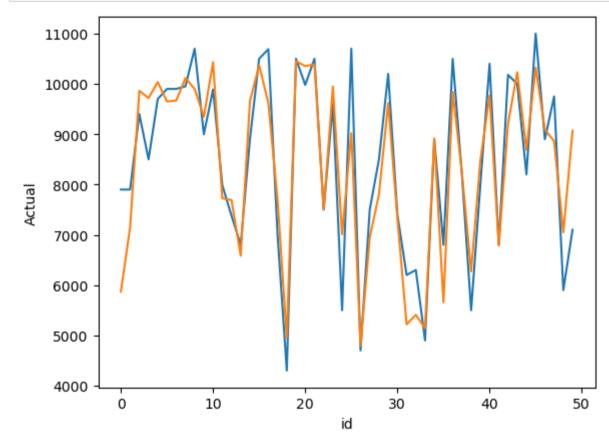
In [72]: results

Out[72]:

	index	Actual	Predicted	id	Difference
0	481	7900	5869.741155	0	2030.258845
1	76	7900	7149.563327	1	750.436673
2	1502	9400	9862.785355	2	-462.785355
3	669	8500	9719.283532	3	-1219.283532
4	1409	9700	10035.895686	4	-335.895686
503	291	10900	10029.070743	503	870.929257
504	596	5699	6297.833772	504	-598.833772
505	1489	9500	10008.285472	505	-508.285472
506	1436	6990	8375.789449	506	-1385.789449
507	575	10900	10368.170257	507	531.829743

508 rows × 5 columns

```
In [73]: 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()
```



### **ElastiNet model**

In [44]: **from** sklearn.linear model **import** ElasticNet

from sklearn.model selection import GridSearchCV

elastic Error

Out[75]: 581390.7642825295

y pred enet=elastic.predict(x test)

In [75]: **from** sklearn.metrics **import** mean squared error

elastic Error=mean squared error(y pred enet,y test)

results['Actual']=y\_test
results['Predicted']=y\_pred\_enet
results=results.reset\_index() #remove the index as ID values
results['id']=results.index

#### In [78]: results

#### Out[78]:

	index	Actual	Predicted	id
0	481	7900	5867.742075	0
1	76	7900	7136.527402	1
2	1502	9400	9865.726723	2
3	669	8500	9722.573593	3
4	1409	9700	10038.936496	4
503	291	10900	10032.030157	503
504	596	5699	6284.484674	504
505	1489	9500	9990.379510	505
506	1436	6990	8380.465651	506
507	575	10900	10370.628731	507

508 rows × 4 columns

In [79]: results["Difference"]=results['Actual']-results['Predicted']#add the column for difference b/w the actual and actual actu

In [80]: results

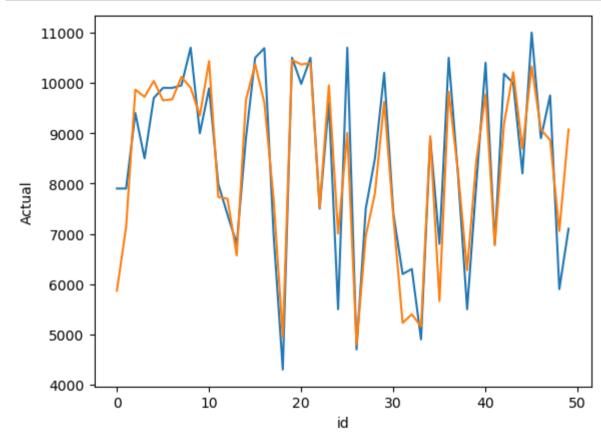
Out[80]:

		index	Actual	Predicted	id	Difference
	0	481	7900	5867.742075	0	2032.257925
	1	76	7900	7136.527402	1	763.472598
	2	1502	9400	9865.726723	2	-465.726723
	3	669	8500	9722.573593	3	-1222.573593
	4	1409	9700	10038.936496	4	-338.936496
5	03	291	10900	10032.030157	503	867.969843
5	04	596	5699	6284.484674	504	-585.484674
5	05	1489	9500	9990.379510	505	-490.379510
5	06	1436	6990	8380.465651	506	-1390.465651
5	07	575	10900	10370.628731	507	529.371269

508 rows × 5 columns

## Plot the data using seaborn and matplotlib libraries

```
In [54]: 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	[	]:	
In	[	]:	
In	[	]:	
In	[	]:	