```
In [1]: import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]: import warnings
warnings.filterwarnings('ignore')

## read a file

In [3]: sai=pd.read\_csv("/home/placement/Downloads/fiat500.csv")

## describe data

In [4]: sai.describe()

Out[4]:

	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

```
ID model engine_power age_in_days
                                         km previous_owners
                                                                            Ion price
                                                                   lat
0 1 lounge
                                       25000
                                                          1 44.907242
                      51
                                 882
                                                                        8.611560
                                                                                 8900
                      51
                                1186
                                       32500
                                                          1 45.666359 12.241890
                                                                                 8800
1 2
        pop
                      74
                                                          1 45.503300 11.417840
2 3
       sport
                                4658 142228
                                                                                 4200
                      51
                                2739 160000
                                                          1 40.633171 17.634609
      lounge
                                                                                 6000
4 5
        pop
                      73
                                3074 106880
                                                          1 41.903221 12.495650 5700
```

### In [6]: sai.info()

In [5]: sai.head()

Out[5]:

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1538 entries, 0 to 1537
Data columns (total 9 columns):

#	Column	Non-Null Count	Dtype
0	ID	1538 non-null	int64
1	model	1538 non-null	object
2	engine_power	1538 non-null	int64
3	age_in_days	1538 non-null	int64
4	km	1538 non-null	int64
5	previous_owners	1538 non-null	int64
6	lat	1538 non-null	float64
7	lon	1538 non-null	float64
8	price	1538 non-null	int64
	45 . 5 . ( 5 )		

dtypes: float64(2), int64(6), object(1)

memory usage: 108.3+ KB

## maping str into int

In [7]: sai['model']=sai['model'].map({'lounge':1,'pop':2,'sport':3})
sai

Out[7]:

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

1538 rows × 9 columns

# eliminating columns

In [8]: sai.drop(['lat','lon','ID'],axis=1)

Out[8]:

	model	engine_power	age_in_days	km	previous_owners	price
0	1	51	882	25000	1	8900
1	2	51	1186	32500	1	8800
2	3	74	4658	142228	1	4200
3	1	51	2739	160000	1	6000
4	2	73	3074	106880	1	5700
1533	3	51	3712	115280	1	5200
1534	1	74	3835	112000	1	4600
1535	2	51	2223	60457	1	7500
1536	1	51	2557	80750	1	5990
1537	2	51	1766	54276	1	7900

1538 rows × 6 columns

# creating dummies

In [9]: pd.get\_dummies(sai)

Out[9]:

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

1538 rows × 9 columns

```
In [10]: y=sai['price']
    x=sai.drop('price',axis=1)
    x
```

Out[10]:

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

1538 rows × 8 columns

# split Train&test

```
In [11]: 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 [12]: x\_test.head(10)

Out[12]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	lon
481	482	2	51	3197	120000	2	40.174702	18.167629
76	77	2	62	2101	103000	1	45.797859	8.644440
1502	1503	1	51	670	32473	1	41.107880	14.208810
669	670	1	51	913	29000	1	45.778591	8.946250
1409	1410	1	51	762	18800	1	45.538689	9.928310
1414	1415	1	51	762	39751	1	41.903221	12.495650
1089	1090	1	51	882	33160	1	45.778999	12.997090
1507	1508	1	51	701	17324	1	45.556549	9.534470
970	971	1	51	701	29000	1	36.855839	14.760470
1198	1199	1	51	1155	38000	1	41.239281	13.933020

In [13]: x\_train.head()

Out[13]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	lon
527	528	1	51	425	13111	1	45.022388	7.58602
129	130	1	51	1127	21400	1	44.332531	7.54592
602	603	2	51	2039	57039	1	40.748241	14.52835
331	332	1	51	1155	40700	1	42.143860	12.54016
323	324	1	51	425	16783	1	41.903221	12.49565

In [14]: x\_train.shape

Out[14]: (1030, 8)

```
In [15]: y_train.head()
Out[15]: 527
                9990
         129
               9500
         602
               7590
         331
               8750
         323
               9100
         Name: price, dtype: int64
In [16]: y_test.head()
Out[16]: 481
                7900
                7900
         76
         1502
                9400
         669
                8500
                9700
         1409
         Name: price, dtype: int64
         linear regression
```

LinearRegression()

```
In [18]: vpred=reg.predict(x test)
         vpred
Out[18]: array([ 5944.42227279,
                                 7382.19406516,
                                                 9714.71708819, 9775.44311825,
                10026.35039712,
                                 9526.60903453,
                                                 9728.62372234, 10094.04177203,
                 9634.26497953,
                                 9227.25952945, 10449.70113586, 7792.84946168,
                 7686.35026828,
                                 6404.97574199,
                                                 9519.56733619, 10398.89844376,
                                                 4682.48932174, 10553.64836355,
                 9386.04052678,
                                 7767.75450844,
                10456.95448735, 10419.26714531,
                                                 7673.16408257, 10003.9826247,
                 7110.92931256,
                                 9091.37732745,
                                                 4953.12222998, 6976.50459799,
                                                 7328.87928145,
                 7808.74298776,
                                 9656.97773957,
                                                                 5336.18956348,
                                                 8981.68582577,
                 5581.53931803,
                                 5133.29004315,
                                                                 5698.30653331,
                10010.97201748,
                                 8329.04920479,
                                                 6210.38005208,
                                                                 8489.42650549,
                 9671.42346301,
                                 6962.22983159,
                                                 8870.19517156, 10152.36356357,
                 8601.72642798, 10155.20812683,
                                                 9163.50558976, 8850.10268988,
                                 9040.21569826,
                                                 9456.38185771, 10380.46653323,
                 7078.34217599,
                10089.95326992,
                                 6929.11259302,
                                                 9675.4468094 .
                                                                 9481.41110019,
                 9400.41281841. 10527.37888794.
                                                 9818.84750332.
                                                                 7347.7283919 .
                 9959.54747529,
                                 7072.02962713,
                                                 9956.12264612,
                                                                 7229.742413
                 6479.8942209 ,
                                 9714.46007894,
                                                 9829.86290779,
                                                                 8667.69380715,
                                 6472.87716903,
                                                 7863.97818584,
                 8487.87151048,
                                                                 6662.3846006
                 8245.10375249, 10522.64398642,
                                                 7421.87683441,
                                                                 8615.1021104
In [19]: from sklearn.metrics import r2 score
         r2 score(y test, ypred)
Out[19]: 0.8395593175117777
In [20]:
         import math
         math.sqrt(0.8395593175117777)
Out[20]: 0.9162746954444272
         from sklearn.metrics import mean squared error as ns
In [21]:
         ns(y test,ypred)
```

Out[21]: 589208.2941160082

In [23]: results=pd.DataFrame(columns=['price','predicted'])
 results['price']=y\_test
 results['predicted']=ypred
 results=results.reset\_index()
 results['ID']=results.index
 results.head(150)

#### Out[23]:

	index	price	predicted	ID
0	481	7900	5944.422273	0
1	76	7900	7382.194065	1
2	1502	9400	9714.717088	2
3	669	8500	9775.443118	3
4	1409	9700	10026.350397	4
145	435	10900	10488.151344	145
146	615	10200	9985.171711	146
147	1274	9990	9692.659509	147
148	78	10900	10719.228742	148
149	1167	6900	7562.688963	149

150 rows × 4 columns

```
In [24]: results['actual price']=results.apply(lambda column:column.price-column.predicted,axis=1)
results
```

Out[24]:

		index	price	predicted	ID	actual price
	0	481	7900	5944.422273	0	1955.577727
	1	76	7900	7382.194065	1	517.805935
	2	1502	9400	9714.717088	2	-314.717088
	3	669	8500	9775.443118	3	-1275.443118
	4	1409	9700	10026.350397	4	-326.350397
į	503	291	10900	10096.821809	503	803.178191
ţ	504	596	5699	6397.963015	504	-698.963015
į	505	1489	9500	10104.531307	505	-604.531307
ţ	506	1436	6990	8228.184595	506	-1238.184595
į	507	575	10900	10312.394358	507	587.605642

508 rows × 5 columns

```
In [25]:
''''sns.lineplot(x='ID',y='price',data=results.head(50))
sns.lineplot(x='ID',y='predicted',data=results.head(50))
plt.plot()'''
```

```
Out[25]: "'sns.lineplot(x='ID',y='price',data=results.head(50))\nsns.lineplot(x='ID',y='predicted',data=results.head(50))\npl
t.plot()"
```

# ridge algorithm

```
In [26]: from sklearn.model selection import GridSearchCV
         from sklearn.linear model import Ridge
         alpha = [1e-15, 1e-\overline{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[26]:
          ▶ GridSearchCV
           ► estimator: Ridge
                ► Ridge
In [27]: ridge regressor.best params
Out[27]: {'alpha': 30}
In [28]: ridge=Ridge(alpha=30)
         ridge.fit(x train,y train)
Out[28]:
                Ridge
          Ridge(alpha=30)
```

```
In [29]: ypred=ridge.predict(x test)
         ypred
Out[29]: array([ 5935.946929
                                7391.09263342,
                                                9713.38936976, 9772.39163591,
                10023.47312697,
                                9525.50186705,
                                                9722.65710008, 10091.63069299,
                 9636.73096762, 9224.80526688, 10447.79862925, 7786.80716239,
                 7678.19575064,
                                6421.69337375,
                                                9518.10281958, 10397.95637713,
                 9423.49349618, 7756.23104841,
                                                4710.38423862, 10549.78058093,
                10437.24157043, 10418.31826122,
                                                7632.07525135, 10001.0098366
                 7105.59647562, 9108.45900086,
                                                4943.04924745, 6968.66299074,
                 7803.8514556 ,
                                9652.86865587, 7322.65097059,
                                                                5323.78883956,
                                                8941.8991792 ,
                 5582.95352334,
                                5112.19802844,
                                                                5689.25952661,
                10025.39399906,
                                8301.88195122,
                                                6203.90223358,
                                                                8504.37941863,
                 9670.09019089,
                                6971.5463123 ,
                                                8907.49429479, 10170.87993833,
                 8596.94188726, 10157.76054033,
                                                9179.69547237, 8847.52279911,
                 7067.90650238, 9037.86413624,
                                                9455.08436147, 10377.61732563,
                10088.89631974. 6940.81914325.
                                                9673.96523836.
                                                                9499.69113131.
                 9434.42007127. 10524.62886148.
                                                9814.37143871.
                                                                7358.73006024.
                 9956.75151813, 7063.75881413,
                                                9953.33251064,
                                                                7221.0307355
                 6469.57255928, 9716.86980556,
                                                9827.02367203,
                                                                8681.78718364,
                 8483.20353285,
                                6462.42679159.
                                                7854.31330446,
                                                                6673.32795121,
                 8241.20718281, 10518.84646819,
                                                7414.525471
                                                                8608.19638711,
```

### mean squared error

```
In [30]: from sklearn.metrics import mean_squared_error
Ridge_Error=mean_squared_error(ypred,y_test)
Ridge_Error
```

Out[30]: 586211.7946814292

### efficiency

```
In [31]: from sklearn.metrics import r2_score
r2_score(y_test,ypred)
```

Out[31]: 0.8403752605647871

```
In [32]: results=pd.DataFrame(columns=['price','predicted'])
    results['price']=y_test
    results['predicted']=ypred
    results=results.reset_index()
    results['ID']=results.index
    results.head(10)
```

#### Out[32]:

	index	price	predicted	ID
0	481	7900	5935.946929	0
1	76	7900	7391.092633	1
2	1502	9400	9713.389370	2
3	669	8500	9772.391636	3
4	1409	9700	10023.473127	4
5	1414	9900	9525.501867	5
6	1089	9900	9722.657100	6
7	1507	9950	10091.630693	7
8	970	10700	9636.730968	8
9	1198	8999	9224.805267	9

## ploting overall

```
In [33]:
    ''''sns.lineplot(x='ID',y='price',data=results.head(50))
    sns.lineplot(x='ID',y='predicted',data=results.head(50))
    plt.plot()'''
```

## elastic regression

```
In [34]: from sklearn.linear model import ElasticNet
         from sklearn.model selection import GridSearchCV
         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[34]:
                GridSearchCV
          ► estimator: ElasticNet
                ▶ ElasticNet
In [35]: elastic regressor.best params
Out[35]: {'alpha': 0.01}
In [36]: elastic=ElasticNet(alpha=0.01)
         elastic.fit(x train,y train)
Out[36]:
                ElasticNet
         ElasticNet(alpha=0.01)
```

```
vpred
                 9365.0016605 ,
                                 9943.36741086,
                                                 8304.33332769,
                                                                  7894.09163625,
                10346.13077992,
                                 5340.9231343 ,
                                                 9766.77567364, 10221.32941809,
                10326.30612878,
                                                 9223.98290751,
                                 9192.79866469.
                                                                 9701.78967137.
                 5640.27515647,
                                 5073.15709356,
                                                 4649.52240787,
                                                                 9639.46554546,
                 6095.21704071,
                                 9868.06349596, 10037.63612681,
                                                                 4934.93522379,
                 8008.61312299,
                                 9677.85950355,
                                                 5896.78814422, 10120.24468547,
                 5386.85309264,
                                 9602.08238956, 10147.97161034, 10076.0201682 ,
                 9578.94736471,
                                 4916.53038674,
                                                 5799.38540503,
                                                                 7183.73138185,
                10035.06741378, 10401.16117446, 10039.59883594,
                                                                  7784.32777363,
                 8717.02851279, 10060.02797243, 10226.30832459,
                                                                 9842.00228195,
                 8362.17553066,
                                 9404.22732378,
                                                 8631.8628269 ,
                                                                 9835.44577072,
                 9709.73205232,
                                 9722.22666121,
                                                 6847.99378527,
                                                                 7325.98238042,
                                 9932.5865531 ,
                 8752.57070479,
                                                 9665.27227701, 10491.77865094,
                 8206.01051332.
                                 6834.46798617.
                                                 9868.21500226.
                                                                 8832.18345989.
                 9768.29853981. 10359.88100206. 10356.74695473.
                                                                 9961.10735251.
                                 9875.4541559 ,
                                                 9211.95577914, 10118.72619683,
                 9314.97450128,
                                                 8804.74165191, 10276.04473909,
                                 6067.65265801.
                 7935.41408168,
                 5789.55515251, 10162.35930573,
                                                 9570.83294736,
                                                                 7797.56435077,
                 9443.89967275.
                                 7405.76504525. 10372.00554671.
                                                                  9983.42468188,
         from sklearn.metrics import mean squared error
In [38]:
         e=mean squared error(ypred,y test)
```

In [37]: vpred=elastic.predict(x test)

Out[38]: 588604.4467931123

Out[39]: 0.8397237443835166

In [39]: from sklearn.metrics import r2\_score
r2 score(y test,ypred)

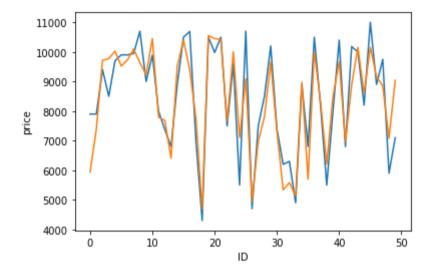
In [40]: results=pd.DataFrame(columns=['price','predicted'])
 results['price']=y\_test
 results['predicted']=ypred
 results=results.reset\_index()
 results['ID']=results.index
 results.head(10)

#### Out[40]:

	index	price	predicted	ID
0	481	7900	5942.632146	0
1	76	7900	7383.882687	1
2	1502	9400	9714.493807	2
3	669	8500	9774.901904	3
4	1409	9700	10025.845278	4
5	1414	9900	9526.430700	5
6	1089	9900	9727.540523	6
7	1507	9950	10093.624606	7
8	970	10700	9634.735077	8
9	1198	8999	9226.824793	9



Out[43]: []



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