# **REDGE RESSION MODEL:**

**USING FIAT500.CSV** 

In [169]: import pandas as rr
In [170]: data=rr.read\_csv("/home/placement/Desktop/ramaraju/fiat500.csv")

In [171]: data

Out[171]:

	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	pop	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	pop	51	1766	54276	1	40.323410	17.568270	7900

1538 rows × 9 columns

In [172]: data.describe()

Out[172]:

	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

```
In [173]: data.info
Out[173]: <bound method DataFrame.info of</pre>
                                                           model engine power
                                                      ID
                                                                                  age in days
                                                                                                        previous owners \
                    1 lounge
                                           51
           0
                                                        882
                                                              25000
                                                       1186
                                                              32500
           1
                    2
                                           51
                                                                                     1
                           qoq
                                                       4658
                                                             142228
                     3
                                           74
                         sport
           3
                       lounge
                                           51
                                                       2739
                                                             160000
                                                                                     1
                                           73
           4
                    5
                                                       3074
                                                             106880
                           pop
                                                                                     1
                           . . .
           . . .
                  . . .
                                                        . . .
                                                                 . . .
          1533
                 1534
                                           51
                                                       3712
                                                             115280
                                                                                     1
                         sport
          1534
                 1535
                       lounge
                                           74
                                                       3835
                                                             112000
          1535
                 1536
                                           51
                                                       2223
                                                              60457
                                                                                     1
                           pop
          1536
                 1537
                                           51
                                                       2557
                                                              80750
                                                                                     1
                       lounge
          1537 1538
                                           51
                                                       1766
                                                              54276
                                                                                     1
                           pop
                       lat
                                         price
                                   lon
                 44.907242
                              8.611560
                                          8900
           0
                 45.666359
                             12.241890
                                          8800
           1
           2
                 45.503300
                             11.417840
                                          4200
                            17.634609
           3
                 40.633171
                                          6000
                 41.903221
                             12.495650
                                          5700
           4
           . . .
                        . . .
                                    . . .
                                           . . .
          1533
                 45.069679
                              7.704920
                                          5200
          1534
                 45.845692
                              8.666870
                                          4600
          1535
                 45.481541
                              9.413480
                                          7500
          1536
                 45.000702
                              7.682270
                                          5990
                 40.323410
                             17.568270
                                          7900
           1537
           [1538 rows x 9 columns]>
In [174]: | data1=data.drop(["lat","lon","ID"],axis=1)
In [175]: data1=rr.get dummies(data1)
```

In [176]: data1

Out[176]:

	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 [177]: z=data1.loc[(data.model=="lounge")]
```

In [178]: z

Out[178]:

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

```
In [180]: y
Out[180]: 0
                    8900
                    6000
          6
                  10750
                   9190
          11
                  10990
                   . . .
          1528
                   5500
          1529
                   9900
          1530
                  10800
          1534
                   4600
          1536
                   5990
          Name: price, Length: 1094, dtype: int64
```

In [181]: x

### Out[181]:

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

1094 rows × 7 columns

In [184]: x\_train.head(5)

#### Out[184]:

	engine_power	age_in_days	km	previous_owners	model_lounge	model_pop	model_sport
441	51	762	36448	1	1	0	0
701	51	701	27100	1	1	0	0
695	51	3197	51083	1	1	0	0
1415	51	670	33000	1	1	0	0
404	51	456	14000	1	1	0	0

## Out[185]:

	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 [186]: 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: I
          ll-conditioned matrix (rcond=1.1816e-27): 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: I
          ll-conditioned matrix (rcond=1.23704e-27): 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: I
          ll-conditioned matrix (rcond=1.18103e-27): 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: I
          ll-conditioned matrix (rcond=1.21179e-27): 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: I
          ll-conditioned matrix (rcond=1.23074e-27): 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: I
          ll-conditioned matrix (rcond=1.1816e-22): 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: I
          ll-conditioned matrix (rcond=1.23704e-22): 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: I
          ll-conditioned matrix (rcond=1.18103e-22): 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: I
          ll-conditioned matrix (rcond=1.21179e-22): 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: I
```

```
ll-conditioned matrix (rcond=1.23074e-22): 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: I
          ll-conditioned matrix (rcond=1.1816e-20): 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: I
          ll-conditioned matrix (rcond=1.23704e-20): 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: I
          ll-conditioned matrix (rcond=1.18103e-20): 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: I
          ll-conditioned matrix (rcond=1.21179e-20): 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: I
          ll-conditioned matrix (rcond=1.23074e-20): result may not be accurate.
            return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
Out[186]:
             GridSearchCV
           ▶ estimator: Ridge
                 ▶ Ridge
In [187]: ridge regressor.best params
Out[187]: {'alpha': 30}
In [188]: ridge=Ridge(alpha=30)
          ridge.fit(x train,y train)
          y pred ridge=ridge.predict(x test)
In [189]: from sklearn.metrics import mean squared error
          Ridge Error=mean squared error(y pred ridge,y test)
          Ridge Error
Out[189]: 519771.8129989745
```

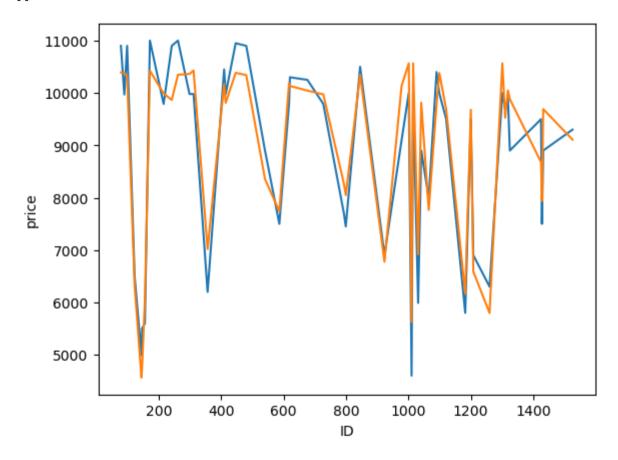
### Out[191]:

	price	predicted	ID
676	10250	10045.347779	676
215	9790	9989.171535	215
146	5500	4769.099603	146
1319	9900	10048.683238	1319
1041	8900	9813.944798	1041
1425	9500	8678.143561	1425
409	10450	10173.797921	409
617	9790	10180.627008	617
1526	9300	9107.315259	1526
1010	4600	5625.007407	1010
1301	10000	10565.711088	1301
923	6900	6776.128155	923
1200	9500	9677.360191	1200
845	10500	10348.971360	845
799	7450	8049.201047	799

```
In [192]: #extract column syntax.
    #data2=x.loc[:,"model_lounge"]
In [196]: #data2
In []: #data2=rr.get_dummies(data2) =>produce("model_longue")
```

```
In [198]: 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[198]: []



In [ ]: