```
In [1]: import pandas as pd
In [2]: data=pd.read_csv("/home/placement/Desktop/reddy/fiat500.csv")
In [3]: data.describe()
```

# Out[3]:

	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 [4]: data.tail(10)

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	ID	model	engine_power	age_in_days	km	previous_owners	lat	lon	price
152	<b>B</b> 1529	lounge	51	2861	126000	1	43.841980	10.51531	5500
152	<b>9</b> 1530	lounge	51	731	22551	1	38.122070	13.36112	9900
153	<b>0</b> 1531	lounge	51	670	29000	1	45.764648	8.99450	10800
153	<b>1</b> 1532	sport	73	4505	127000	1	45.528511	9.59323	4750
153	<b>2</b> 1533	pop	51	1917	52008	1	45.548000	11.54947	9900
153	<b>3</b> 1534	sport	51	3712	115280	1	45.069679	7.70492	5200
153	<b>4</b> 1535	lounge	74	3835	112000	1	45.845692	8.66687	4600
153	<b>5</b> 1536	pop	51	2223	60457	1	45.481541	9.41348	7500
153	<b>6</b> 1537	lounge	51	2557	80750	1	45.000702	7.68227	5990
153	<b>7</b> 1538	pop	51	1766	54276	1	40.323410	17.56827	7900

```
In [6]: data1
Out[6]:
                model engine_power age_in_days
                                                  km previous owners price
             0 lounge
                                51
                                           882
                                                25000
                                                                   1 8900
             1
                  pop
                                51
                                          1186
                                                32500
                                                                   1 8800
                                74
                                                                   1 4200
             2
                 sport
                                          4658 142228
                                51
                                          2739 160000
               lounge
                                                                   1 6000
                                73
                                          3074 106880
                                                                   1 5700
                  pop
          1533
                                51
                                          3712 115280
                                                                   1 5200
                 sport
                                74
                                          3835
                                               112000
                                                                      4600
          1534
                lounge
          1535
                                51
                                                                   1 7500
                  pop
                                          2223
                                                60457
          1536
                                51
                                          2557
                                                                      5990
                lounge
                                                80750
          1537
                                51
                                          1766
                                                                   1 7900
                  pop
                                                54276
         1538 rows × 6 columns
In [7]: data1['model']=data1['model'].map({'lounge':1,'pop':2,'sport':3})
```

In [8]: data1

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

In [10]: datal=pd.get\_dummies(datal)

In [11]: data1

Out[11]:

	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

```
In [12]: y=data1['price']
x=data1.drop('price',axis=1)
```

```
In [13]: y
Out[13]: 0
                 8900
                 8800
         2
                 4200
         3
                 6000
                 5700
         4
                  . . .
         1533
                 5200
         1534
                 4600
         1535
                 7500
         1536
                 5990
         1537
                 7900
         Name: price, Length: 1538, dtype: int64
```

# In [14]: x

### Out[14]:

_		model	engine_power	age_in_days	km	previous_owners
_	0	1	51	882	25000	1
	1	2	51	1186	32500	1
	2	3	74	4658	142228	1
	3	1	51	2739	160000	1
	4	2	73	3074	106880	1
	1533	3	51	3712	115280	1
	1534	1	74	3835	112000	1
	1535	2	51	2223	60457	1
	1536	1	51	2557	80750	1
	1537	2	51	1766	54276	1

1538 rows × 5 columns

```
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)
In [16]: x test.head(5)
Out[16]:
                model engine_power age_in_days
                                                 km previous_owners
                    2
                                         3197 120000
                                                                 2
            481
                               51
                                         2101 103000
             76
                    2
                               62
                                                                 1
           1502
                    1
                               51
                                               32473
                                                                 1
                                          670
            669
                    1
                               51
                                          913
                                               29000
                                                                 1
           1409
                    1
                               51
                                          762
                                               18800
                                                                 1
In [17]: x_train.shape
Out[17]: (1030, 5)
In [18]: y_train.shape
Out[18]: (1030,)
In [19]: x train.head()
Out[19]:
               model engine_power age_in_days
                                               km previous owners
           527
                   1
                               51
                                         425 13111
                                                                1
           129
                   1
                               51
                                        1127
                                             21400
                                                                1
           602
                   2
                               51
                                        2039
                                             57039
                                                                1
           331
                               51
                                             40700
                   1
                                        1155
                                                                1
           323
                   1
                               51
                                         425 16783
                                                                1
```

```
In [20]: y train.head()
Out[20]: 527
                  9990
          129
                  9500
          602
                  7590
          331
                  8750
          323
                  9100
          Name: price, dtype: int64
In [21]: x_test.head()
Out[21]:
                model engine_power age_in_days
                                                 km previous_owners
                    2
                               51
                                        3197 120000
                                                                 2
            481
                               62
                                        2101 103000
             76
                    2
                                                                1
           1502
                    1
                               51
                                         670
                                              32473
                                                                1
                                              29000
                                                                1
            669
                               51
                                         913
                    1
                               51
                                              18800
                                                                1
           1409
                    1
                                         762
In [22]: y_test.head()
Out[22]: 481
                   7900
          76
                   7900
          1502
                   9400
          669
                   8500
          1409
                   9700
          Name: price, dtype: int64
          #linear regression
```

```
In [23]: | from sklearn.linear model import LinearRegression
         reg=LinearRegression()
         req.fit(x train,y train)
Out[23]: 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 nbyiewer.org.
In [24]: ypred=reg.predict(x test)
In [25]: ypred
Out[25]: array([ 5994.51703157,
                                   7263.58726658,
                                                                    9699.31627673,
                                                    9841.90754881,
                 10014.19892635.
                                   9630.58715835.
                                                    9649.4499026 , 10092.9819664 ,
                  9879.19498711,
                                   9329.19347948, 10407.2964056,
                                                                    7716.91706011,
                  7682.89152522,
                                   6673.95810983,
                                                    9639.42618839, 10346.53679153,
                  9366.53363673,
                                   7707.90063494,
                                                    4727.33552438, 10428.17092937,
                 10359.87663878, 10364.84674179,
                                                    7680.16157493,
                                                                    9927.58506055,
                  7127.7284177 ,
                                   9097.51161986,
                                                    4929.31229715,
                                                                    6940.60225317,
                                                                    5224.05298205,
                  7794.35120591.
                                   9600.43942019,
                                                    7319.85877519.
                  5559.52039134,
                                                                    5659.72968338,
                                   5201.35403287,
                                                    8960.11762682,
                  9915.79926869,
                                   8255.93615893,
                                                    6270.40332834,
                                                                    8556.73835062,
                  9749.72882426,
                                   6873.76758364,
                                                    8951.72659758, 10301.95669828,
                                                                    8846.92420399,
                  8674.89268564, 10301.93257222,
                                                    9165.73586068,
                  7044.68964545,
                                   9052.4031418 ,
                                                    9390.75738772, 10267.3912561,
                 10046.90924744,
                                   6855.71260655,
                                                    9761.93338967,
                                                                     9450.05744337,
                  9274.98388541, 10416.00474283,
                                                    9771.10646661,
                                                                    7302.96566423,
                                                                    7134.21944391,
                 10082.61483093,
                                   6996.96553454,
                                                    9829.40534825,
                  6407.26222178,
                                   9971.82132188,
                                                    9757.01618446,
                                                                    8614.84049875,
                  8437.92452169,
                                   6489.24658616,
                                                    7752.65456507,
                                                                    6626.60510856,
                  8329.88998217, 10412.00324329,
                                                    7342.77348105,
                                                                    8543.63624413,
                                  10010 42502651
                                                    7256 06706062
                                                                     NE32 14000E1
In [26]: from sklearn.metrics import r2 score
         r2 score(y test,ypred)
Out[26]: 0.8383895235218546
```

localhost:8888/notebooks/Desktop/ramaraju/linear%2Cridge%2Celastic.ipynb

```
In [27]: from sklearn.metrics import mean squared error as ns
         o=ns(y test,ypred)
Out[27]: 593504.2888137395
In [28]: import math
         math.sgrt(o)
Out[28]: 770.3922954013361
In [29]: | ypred
Out[29]: array([ 5994.51703157,
                                  7263.58726658,
                                                   9841.90754881,
                                                                   9699.31627673,
                 10014.19892635,
                                  9630.58715835,
                                                   9649.4499026 , 10092.9819664 ,
                  9879.19498711,
                                  9329.19347948, 10407.2964056,
                                                                   7716.91706011,
                                                   9639.42618839, 10346.53679153.
                  7682.89152522,
                                  6673.95810983,
                  9366.53363673,
                                  7707.90063494,
                                                   4727.33552438, 10428.17092937,
                 10359.87663878, 10364.84674179,
                                                   7680.16157493,
                                                                   9927.58506055,
                  7127.7284177 ,
                                  9097.51161986,
                                                   4929.31229715,
                                                                   6940.60225317,
                                                   7319.85877519,
                  7794.35120591,
                                  9600.43942019,
                                                                   5224.05298205,
                  5559.52039134,
                                  5201.35403287,
                                                   8960.11762682,
                                                                   5659.72968338,
                                                                   8556.73835062,
                  9915.79926869,
                                  8255.93615893,
                                                   6270.40332834,
                  9749.72882426,
                                  6873.76758364,
                                                   8951.72659758, 10301.95669828,
                  8674.89268564, 10301.93257222,
                                                   9165.73586068,
                                                                   8846.92420399,
                  7044.68964545,
                                  9052.4031418 ,
                                                   9390.75738772, 10267.3912561,
                 10046.90924744,
                                  6855.71260655,
                                                   9761.93338967,
                                                                   9450.05744337,
                 9274.98388541, 10416.00474283,
                                                   9771.10646661,
                                                                   7302.96566423,
                 10082.61483093,
                                  6996.96553454,
                                                   9829.40534825,
                                                                   7134.21944391,
                  6407.26222178,
                                  9971.82132188,
                                                   9757.01618446,
                                                                   8614.84049875,
                  8437.92452169,
                                  6489.24658616,
                                                   7752.65456507,
                                                                   6626.60510856,
                  8329.88998217, 10412.00324329,
                                                   7342.77348105,
                                                                   8543.63624413,
```

```
In [30]: 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[30]:

	index	price	predicted	ID
0	481	7900	5994.517032	0
1	76	7900	7263.587267	1
2	1502	9400	9841.907549	2
3	669	8500	9699.316277	3
4	1409	9700	10014.198926	4
5	1414	9900	9630.587158	5
6	1089	9900	9649.449903	6
7	1507	9950	10092.981966	7
8	970	10700	9879.194987	8
9	1198	8999	9329.193479	9
10	1088	9890	10407.296406	10
11	576	7990	7716.917060	11
12	965	7380	7682.891525	12
13	1488	6800	6673.958110	13
14	1432	8900	9639.426188	14

```
In [31]: Results['price_diff']=Results.apply(lambda row: row.price - row.predicted,axis=1)
```

# In [32]: Results

# Out[32]:

	index	price	predicted	ID	price_diff
0	481	7900	5994.517032	0	1905.482968
1	76	7900	7263.587267	1	636.412733
2	1502	9400	9841.907549	2	-441.907549
3	669	8500	9699.316277	3	-1199.316277
4	1409	9700	10014.198926	4	-314.198926
503	291	10900	10007.364639	503	892.635361
504	596	5699	6390.174715	504	-691.174715
505	1489	9500	10079.478928	505	-579.478928
506	1436	6990	8363.337585	506	-1373.337585
507	575	10900	10344.486077	507	555.513923

508 rows × 5 columns

#ridge regression

```
In [33]: from sklearn.model selection import GridSearchCV
         from sklearn.linear model import Ridge
         #ridae rearession
         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)
Out[33]: GridSearchCV(estimator=Ridge(),
                       param grid={'alpha': [1e-15, 1e-10, 1e-08, 0.0001, 0.001, 0.01, 1,
                                              5, 10, 20, 301})
         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 [34]: ridge regressor.best params
Out[34]: {'alpha': 30}
In [35]: ridge=Ridge(alpha=30)
          ridge.fit(x train,y train)
         y pred ridge=ridge.predict(x test)
In [36]: from sklearn.metrics import mean squared error
         Ridge Error=mean squared error(y pred ridge,y test)
         Ridge Error
Out[36]: 590569.9121697355
```

```
In [37]: from sklearn.metrics import r2_score
    r2_score(y_test,y_pred_ridge)

Out[37]: 0.8391885506165899

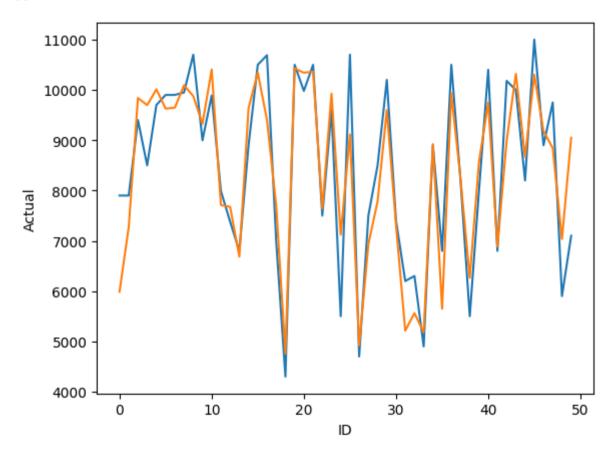
In [38]: Results=pd.DataFrame(columns=['Actual','predicted'])
    Results['Actual']=y_test
    Results['predicted']=y_pred_ridge
    Results=Results.reset_index()
    Results['ID']=Results.index
    Results.head(10)
```

### Out[38]:

	index	Actual	predicted	ID
0	481	7900	5987.682984	0
1	76	7900	7272.490419	1
2	1502	9400	9839.847697	2
3	669	8500	9696.775405	3
4	1409	9700	10012.040862	4
5	1414	9900	9628.286853	5
6	1089	9900	9646.945160	6
7	1507	9950	10090.960592	7
8	970	10700	9877.094341	8
9	1198	8999	9326.088982	9

```
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.plot()
```

#### Out[39]: []



#elastic

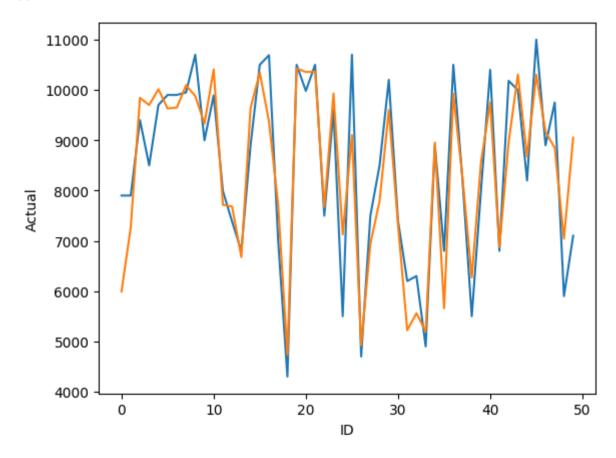
```
In [42]: from sklearn.linear model import ElasticNet
         from sklearn.model selection import GridSearchCV
         elastic = ElasticNet()
         parameters = { 'alpha': [1e-15, 1e-10, 1e-8, 1e-4, 1e-3,1e-2, 1, 5, 10, 20]}
         elastic regressor = GridSearchCV(elastic, parameters)
         elastic regressor.fit(x train, y train)
Out[42]: GridSearchCV(estimator=ElasticNet(),
                       param grid={'alpha': [1e-15, 1e-10, 1e-08, 0.0001, 0.001, 0.01, 1,
                                               5, 10, 20]})
         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 [43]: elastic regressor.best params
Out[43]: {'alpha': 0.01}
In [47]: elastic=ElasticNet(alpha=0.01)
         elastic.fit(x train,y train)
         y pred elastic=elastic.predict(x test)
In [48]: from sklearn.metrics import r2 score
         r2_score(y_test,y_pred_elastic)
Out[48]: 0.8385500526604823
```

$\sim$				$\sim$	
11		-	-	1.I	
v	u	_	ıJ	v	

	index	Actual	predicted	ID
0	481	7900	5993.053059	0
1	76	7900	7265.275818	1
2	1502	9400	9841.546147	2
3	669	8500	9698.864284	3
4	1409	9700	10013.815854	4
5	1414	9900	9630.182678	5
6	1089	9900	9649.005668	6
7	1507	9950	10092.624034	7
8	970	10700	9878.825124	8
9	1198	8999	9328.638538	9

```
In [51]: import seaborn as sns#plot
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.plot()
```

#### Out[51]: []



In [ ]: