```
In [1]: import pandas as pd
import warnings
warnings.filterwarnings("ignore")
```

In [2]: data=pd.read\_csv("/home/placement/Desktop/python/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.info
Out[4]: <bound method DataFrame.info of</pre>
                                                                                 age_in_days
                                                     ID
                                                          model engine power
                                                                                                        previous owners \
                                          51
                                                       882
                                                             25000
         0
                   1 lounge
                                                      1186
                                                             32500
         1
                   2
                                          51
                                                                                    1
                         pop
                                          74
                                                      4658
                                                            142228
                   3
                       sport
         3
                      lounge
                                          51
                                                      2739
                                                            160000
                                                                                    1
                   5
                                          73
         4
                                                      3074
                                                            106880
                                                                                    1
                         pop
                         . . .
                                                       . . .
                                                                . . .
                . . .
                                         . . .
         1533
               1534
                                          51
                                                      3712
                                                            115280
                                                                                    1
                       sport
         1534
               1535
                      lounge
                                          74
                                                      3835
                                                            112000
         1535
               1536
                                          51
                                                      2223
                                                             60457
                                                                                    1
                         pop
         1536
               1537
                      lounge
                                          51
                                                      2557
                                                             80750
                                                                                    1
         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
         3
               40.633171
                           17.634609
                                        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
         1537
               40.323410
                           17.568270
                                        7900
         [1538 rows x 9 columns]>
```

Out[5]:		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

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:		ID	engine_power	age_in_days	km	previous_owners	lat	lon	price	model_lounge	model_pop	model_sport
	0	1	51	882	25000	1	44.907242	8.611560	8900	1	0	0
	1	2	51	1186	32500	1	45.666359	12.241890	8800	0	1	0
	2	3	74	4658	142228	1	45.503300	11.417840	4200	0	0	1
	3	4	51	2739	160000	1	40.633171	17.634609	6000	1	0	0
	4	5	73	3074	106880	1	41.903221	12.495650	5700	0	1	0
					•••							
15	533	1534	51	3712	115280	1	45.069679	7.704920	5200	0	0	1
15	534	1535	74	3835	112000	1	45.845692	8.666870	4600	1	0	0
15	535	1536	51	2223	60457	1	45.481541	9.413480	7500	0	1	0
15	536	1537	51	2557	80750	1	45.000702	7.682270	5990	1	0	0
15	537	1538	51	1766	54276	1	40.323410	17.568270	7900	0	1	0

1538 rows × 11 columns

```
In [7]: y=data['price']
x=data.drop('price',axis=1)
```

```
In [8]: y
Out[8]: 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 [9]: x

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

1538 rows × 10 columns

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

Out[11]:		ID	engine_power	age_in_days	km	previous_owners	lat	lon	model_lounge	model_pop	model_sport
	481	482	51	3197	120000	2	40.174702	18.167629	0	1	0
	76	77	62	2101	103000	1	45.797859	8.644440	0	1	0
	1502	1503	51	670	32473	1	41.107880	14.208810	1	0	0
	669	670	51	913	29000	1	45.778591	8.946250	1	0	0
	1409	1410	51	762	18800	1	45.538689	9.928310	1	0	0

```
In [12]: 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)
```

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 [13]: 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[13]: 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 [14]: elastic regressor.best params
Out[14]: {'alpha': 0.01}
In [15]: elastic=ElasticNet(alpha=30)
         elastic.fit(x train,y train)
         ypred=elastic.predict(x test)
In [16]: from sklearn.metrics import r2 score
          r2 score(y test,ypred)
Out[16]: 0.8416206414238153
In [17]: from sklearn.metrics import mean squared error
         elastic error=mean squared error(ypred,y test)
         elastic error
Out[17]: 581638.2119710302
 In [ ]:
```