```
In [178]: import pandas as pd
In [179]: import warnings
    warnings.filterwarnings('ignore')
In [180]: data=pd.read_csv("/home/placement/Downloads/fiat500.csv")
In [181]: data.describe()
```

Out[181]:

	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 [182]: data.info()
          <class 'pandas.core.frame.DataFrame'>
          RangeIndex: 1538 entries, 0 to 1537
          Data columns (total 9 columns):
                                Non-Null Count Dtype
               Column
               _ _ _ _ _
               ID
                                1538 non-null
           0
                                                int64
               model
                                                 object
                                1538 non-null
               engine power
                                1538 non-null
                                                 int64
               age_in_days
                                1538 non-null
                                                 int64
           4
               km
                                1538 non-null
                                                 int64
               previous_owners 1538 non-null
                                                int64
               lat
                                1538 non-null
                                                float64
           7
               lon
                                1538 non-null
                                                float64
               price
                                1538 non-null
                                                int64
          dtypes: float64(2), int64(6), object(1)
          memory usage: 108.3+ KB
```

# In [183]: data.head()

#### Out[183]:

	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

```
In [184]: data1=data.loc[(data.previous_owners==1)]
```

In [185]: data1

Out[185]:

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

1389 rows × 9 columns

```
In [186]: datal=data.drop(['ID','lat','lon'],axis=1)
```

In [187]: data1

Out[187]:

	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 [188]: datal=pd.get\_dummies(data)

In [189]: data1

Out[189]:

	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
1533	1534	51	3712	115280	1	45.069679	7.704920	5200	0	0	1
1534	1535	74	3835	112000	1	45.845692	8.666870	4600	1	0	0
1535	1536	51	2223	60457	1	45.481541	9.413480	7500	0	1	0
1536	1537	51	2557	80750	1	45.000702	7.682270	5990	1	0	0
1537	1538	51	1766	54276	1	40.323410	17.568270	7900	0	1	0

1538 rows × 11 columns

```
In [190]: data1.shape
Out[190]: (1538, 11)
In [191]: y=data1['price']
x=data1.drop('price',axis=1)
```

```
In [192]: y
Out[192]: 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 [193]: x

## Out[193]:

	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 [194]: 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 [195]: x\_test.head()

Out[195]:

	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 [196]: y\_test.head()

Out[196]: 481 7900 76 7900 1502 9400 669 8500 1409 9700

Name: price, dtype: int64

In [197]: x\_train.head()

Out[197]:

	ID	engine_power	age_in_days	km	previous_owners	lat	lon	model_lounge	model_pop	model_sport
527	528	51	425	13111	1	45.022388	7.58602	1	0	0
129	130	51	1127	21400	1	44.332531	7.54592	1	0	0
602	603	51	2039	57039	1	40.748241	14.52835	0	1	0
331	332	51	1155	40700	1	42.143860	12.54016	1	0	0
323	324	51	425	16783	1	41.903221	12.49565	1	0	0

```
In [198]: y train.head()
Out[198]: 527
                 9990
          129
                 9500
                 7590
          602
          331
                 8750
          323
                 9100
          Name: price, dtype: int64
In [199]: 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[199]:
                 GridSearchCV
           ▶ estimator: ElasticNet
                 ▶ ElasticNet
In [200]: elastic_regressor.best_params_
Out[200]: {'alpha': 0.01}
In [201]: elastic=ElasticNet(alpha=.01)
          elastic.fit(x_train,y_train)
          y pred elastic=elastic.predict(x test)
```

```
In [202]:
          y pred elastic
Out[202]: array([ 5818.88155606,
                                   7251.60740134,
                                                   9741.37548309.
                                                                    9798.17563202.
                 10054.18656906.
                                   9551.03709384.
                                                    9756.60308305. 10122.24386003.
                  9655.23079132.
                                   9250.43675403. 10477.46946422.
                                                                    7805.98706383.
                  7703.41076005,
                                   6299.65982145,
                                                   9544.86952947, 10422.52128897,
                                   7754.80253699,
                  9622.08375661,
                                                    4897.38480628, 10580.47637966,
                 10461.71330862, 10442.89200323,
                                                   7512.81872938, 10027.42619282,
                  6990.9795985 ,
                                   8993.93966292,
                                                    4822.9274055 ,
                                                                    6987.38971162,
                  7821.74361059,
                                   9682.14401582,
                                                   7342.84571741,
                                                                    5338.98378321,
                  5422.36411921,
                                   5088.69094616,
                                                   8964.54155191,
                                                                    5701.00133273,
                  9923.63970799,
                                                                    8392.88958456,
                                   8329.65576797,
                                                    6219.5421374 ,
                  9695.35125166,
                                   6862.17433129,
                                                    9106.3590491 , 10067.46187307,
                  8620.73186465, 10175.36762819,
                                                                    8866.57789002,
                                                    9067.11601592,
                                                    9474.38711846, 10405.31440756,
                  7092.28977184,
                                   9057.74520111,
                 10112.23689137,
                                   6823.98653466,
                                                    9699.84010068,
                                                                    9386.45543089,
                  9637.09234337, 10553.05108845,
                                                    9846.08937468,
                                                                    7250.04609281,
                                   7082.51579887,
                                                                    7243.17422389.
                  9989.41187642,
                                                    9976.61490792,
                  6488.79520193,
                                   9738.09464099,
                                                    9852.77779753,
                                                                    8572.18811531,
                  8505.72502159,
                                   6482.56240442,
                                                    7881.15444662,
                                                                    6870.90829793,
                  8262.43238047, 10550.05609925.
                                                    7433.16232868.
                                                                    8636.30752919.
In [203]: from sklearn.metrics import r2 score
          r2 score(y test,y pred elastic)
Out[203]: 0.8429739684420192
In [204]: from sklearn.metrics import mean squared error
          elastic Error=mean squared error(y pred elastic,y test)
          elastic Error
Out[204]: 576668.2037947337
```

In [205]: Results=pd.DataFrame(columns=['Actual','predicted'])
 Results['Actual']=y\_test
 Results['Predicted']=y\_pred\_elastic
 Results=Results.reset\_index()
 Results['Id']=Results.index
 Results

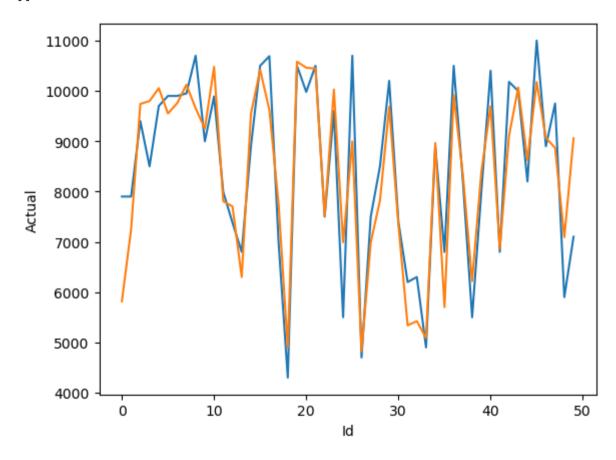
#### Out[205]:

index	Actual	predicted	Predicted	ld
481	7900	NaN	5818.881556	0
76	7900	NaN	7251.607401	1
1502	9400	NaN	9741.375483	2
669	8500	NaN	9798.175632	3
1409	9700	NaN	10054.186569	4
291	10900	NaN	10120.713199	503
596	5699	NaN	6291.601668	504
1489	9500	NaN	10020.222896	505
1436	6990	NaN	8247.810365	506
575	10900	NaN	10337.015702	507
	481 76 1502 669 1409  291 596 1489 1436	481 7900 76 7900 1502 9400 669 8500 1409 9700 291 10900 596 5699 1489 9500 1436 6990	481 7900 NaN 76 7900 NaN 1502 9400 NaN 669 8500 NaN 1409 9700 NaN 291 10900 NaN 596 5699 NaN 1489 9500 NaN 1436 6990 NaN	481 7900 NaN 5818.881556 76 7900 NaN 7251.607401 1502 9400 NaN 9741.375483 669 8500 NaN 9798.175632 1409 9700 NaN 10054.186569 291 10900 NaN 10120.713199 596 5699 NaN 6291.601668 1489 9500 NaN 10020.222896 1436 6990 NaN 8247.810365

508 rows × 5 columns

```
In [206]: 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[206]: []



In [ ]: 1