```
In [1]: import pandas as pd
         import warnings
         warnings.filterwarnings("ignore")
         data = pd.read csv("/home/placement/Downloads/fiat500.csv")
In [3]: data.describe()
                         ID engine power age in days
                                                                   km previous owners
                                                                                                                          price
                                                                                                 lat
Out[3]:
                                                                                                              lon
         count 1538.000000
                                                           1538.000000
                                                                                        1538.000000
                               1538.000000
                                            1538.000000
                                                                            1538.000000
                                                                                                     1538.000000
                                                                                                                   1538.000000
                 769.500000
                                           1650.980494
                                                         53396.011704
                                                                               1.123537
                                                                                           43.541361
                                                                                                       11.563428
                                                                                                                   8576.003901
                                 51.904421
          mean
            std
                 444.126671
                                  3.988023
                                           1289.522278
                                                          40046.830723
                                                                               0.416423
                                                                                            2.133518
                                                                                                         2.328190
                                                                                                                   1939.958641
                   1.000000
                                 51.000000
                                             366.000000
                                                          1232.000000
                                                                               1.000000
                                                                                           36.855839
                                                                                                         7.245400
           min
                                                                                                                   2500.000000
                 385.250000
           25%
                                 51.000000
                                             670.000000
                                                         20006.250000
                                                                               1.000000
                                                                                           41.802990
                                                                                                         9.505090
                                                                                                                   7122.500000
                 769.500000
                                                                               1.000000
           50%
                                 51.000000
                                            1035.000000
                                                         39031.000000
                                                                                           44.394096
                                                                                                        11.869260
                                                                                                                   9000.000000
               1153.750000
                                                                               1.000000
                                                                                           45.467960
           75%
                                 51.000000
                                            2616.000000
                                                          79667.750000
                                                                                                        12.769040
                                                                                                                  10000.000000
           max 1538.000000
                                 77.000000
                                           4658.000000 235000.000000
                                                                               4.000000
                                                                                           46.795612
                                                                                                        18.365520 11100.000000
         data.head()
In [4]:
            ID model engine power age in days
                                                                                   lat
                                                                                             Ion price
Out[4]:
                                                       km previous owners
                lounge
                                  51
                                                    25000
                                                                            44.907242
                                                                                        8.611560
         0
             1
                                              882
                                                                                                  8900
             2
         1
                                  51
                                             1186
                                                    32500
                                                                            45.666359 12.241890
                                                                                                  8800
                   pop
         2
             3
                                  74
                                             4658
                                                  142228
                                                                            45.503300 11.417840
                                                                                                  4200
                 sport
                lounge
                                  51
                                             2739
                                                   160000
                                                                            40.633171 17.634609
                                                                                                  6000
         4
             5
                                  73
                                             3074 106880
                                                                         1 41.903221 12.495650
                                                                                                  5700
                   pop
```

```
In [5]: data1=data.drop(['lat','lon','ID'],axis=1)
In [6]: data1
              model engine_power age_in_days
                                                  km previous_owners price
Out[6]:
           0 lounge
                                          882
                                               25000
                                                                      8900
                               51
                pop
                               51
                                         1186
                                               32500
                                                                      8800
                                         4658 142228
                                                                      4200
                               74
               sport
                                         2739 160000
                                                                      6000
             lounge
                               51
                                                                      5700
                pop
                               73
                                         3074 106880
         1533
                               51
                                         3712 115280
                                                                      5200
                sport
        1534 lounge
                               74
                                         3835 112000
                                                                      4600
        1535
                               51
                                         2223
                                               60457
                                                                      7500
                pop
        1536 lounge
                               51
                                         2557
                                               80750
                                                                      5990
                                                                   1 7900
        1537
                pop
                               51
                                         1766
                                               54276
        1538 rows × 6 columns
In [7]: data1=pd.get dummies(data1)
In [8]: data1.shape
Out[8]: (1538, 8)
In [9]: data1
```

Out[9]:		engine_power	age_in_days	km	previous_owners	price	model_lounge	model_pop	model_sport
	0	51	882	25000	1	8900	True	False	False
	1	51	1186	32500	1	8800	False	True	False
	2	74	4658	142228	1	4200	False	False	True
	3	51	2739	160000	1	6000	True	False	False
	4	73	3074	106880	1	5700	False	True	False
15	533	51	3712	115280	1	5200	False	False	True
15	534	74	3835	112000	1	4600	True	False	False
15	535	51	2223	60457	1	7500	False	True	False
15	536	51	2557	80750	1	5990	True	False	False
15	537	51	1766	54276	1	7900	False	True	False

1538 rows × 8 columns

```
In [10]: y=data1['price']
In [11]: x = data1.drop('price',axis=1)
In [12]: y
```

```
Out[12]: 0
                  8900
                  8800
         2
                  4200
         3
                  6000
                  5700
                  . . .
         1533
                  5200
         1534
                  4600
         1535
                  7500
         1536
                  5990
         1537
                  7900
         Name: price, Length: 1538, dtype: int64
In [13]: #!pip3 install scikit-learn
In [14]: 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 [15]: x test.head(5)
               engine_power age_in_days
                                            km previous_owners model_lounge model_pop model_sport
Out[15]:
                         51
                                   3197 120000
                                                              2
           481
                                                                        False
                                                                                    True
                                                                                                False
           76
                         62
                                   2101
                                        103000
                                                              1
                                                                        False
                                                                                    True
                                                                                                False
                                                                                                False
          1502
                         51
                                    670
                                          32473
                                                                         True
                                                                                   False
                                                              1
           669
                         51
                                    913
                                          29000
                                                                         True
                                                                                   False
                                                                                                False
                                                              1
          1409
                         51
                                    762
                                          18800
                                                                         True
                                                                                    False
                                                                                                False
In [16]: x train.shape
Out[16]: (1030, 7)
In [17]: y test.head()
```

```
Out[17]: 481
                 7900
         76
                 7900
         1502
                 9400
         669
                 8500
                 9700
         1409
         Name: price, dtype: int64
In [18]: y_train.shape
Out[18]: (1030,)
In [19]: from sklearn.linear model import LinearRegression
In [20]: reg=LinearRegression()
In [21]: reg.fit(x_train,y_train)
Out[21]: ▼ LinearRegression
         LinearRegression()
In [22]: ypred=reg.predict(x test)
In [23]: ypred
```

```
Out[23]: array([ 5867.6503378 , 7133.70142341, 9866.35776216, 9723.28874535,
               10039.59101162.
                                9654.07582608, 9673.14563045, 10118.70728123,
                9903.85952664, 9351.55828437, 10434.34963575, 7732.26255693,
                7698.67240131, 6565.95240435, 9662.90103518, 10373.20344286,
                9599.94844451, 7699.34400418, 4941.33017994, 10455.2719478,
               10370.51555682, 10391.60424404, 7529.06622456, 9952.37340054,
                7006.13845729, 9000.1780961, 4798.36770637, 6953.10376491,
                7810.39767825, 9623.80497535, 7333.52158317, 5229.18705519,
                5398.21541073, 5157.65652129, 8948.63632836, 5666.62365159,
                9822.1231461 , 8258.46551788, 6279.2040404 , 8457.38443276,
                9773.86444066, 6767.04074749, 9182.99904787, 10210.05195479,
                8694.90545226, 10328.43369248, 9069.05761443, 8866.7826029,
                7058.39787506, 9073.33877162, 9412.68162121, 10293.69451263,
               10072.49011135, 6748.5794244 , 9785.95841801, 9354.09969973,
                9507.9444386 , 10443.01608254 , 9795.31884316 , 7197.84932877 ,
               10108.31707235, 7009.6597206, 9853.90699412, 7146.87414965,
                6417.69133992, 9996.97382441, 9781.18795953, 8515.83255277,
                8456.30006203, 6499.76668237, 7768.57829985, 6832.86406122,
                8347.96113362, 10439.02404036, 7356.43463051, 8562.56562053,
                9820.78555199, 10035.83571539, 7370.77198022, 9411.45894006,
               10352.85155564, 8045.21588007, 10446.80664758, 3736.20118868,
               10348.63930496, 10435.96627494, 6167.80169017, 10390.11317804,
                6527.69471073, 9116.4755691, 10484.52829, 9335.69889855,
                6709.57413543, 3390.72353093, 10106.33753331, 9792.46732008,
                6239.49568346,
                                4996.26346266, 9044.38667681, 9868.09959448,
                5484.13199252, 5698.5954821, 10086.86206874, 8115.81693479,
               10392.37800936, 6835.6573351, 6657.61744836, 5738.50576764,
                8896.80120764, 9952.37340054, 10390.28377419, 9419.10788866,
                9082.56591129, 10122.82465116, 10410.00504522, 10151.77663915,
                9714.85367238, 9291.92963633, 10346.99073888, 5384.22311343,
                9772.85146492, 6069.77107828, 9023.26394782, 10220.56195956,
                9238.89392583, 9931.47195375, 8321.42715662, 8377.80491069,
                7528.53327408, 10552.64805598, 10465.02437243, 10110.68940664,
               10238.17869436, 6841.77264488, 9625.64505547, 10412.59988875,
                9653.06224923, 7948.63618724, 9704.82523573, 7971.05970955,
               10399.51752022, 9176.43567301, 5803.03205787, 6698.19524313,
                8257.83550573, 10452.95284574, 9948.66454584, 9789.65062843,
               10582.50828537, 7568.91955482, 6804.97705225, 8065.01292384.
               10310.29143419, 8836.34894739, 8390.05091229, 9582.13932508,
                9745.34784981, 10045.45021387, 10294.09872915, 7145.15315349,
```

```
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```

```
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```

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10092.46332921, 10381.52000388, 9723.92466625, 5996.3331428,
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                 9856.66053994, 9236.22981005, 10092.64052142, 6256.43516278,
                 8592.63841379, 10341.5365957, 5177.96595576, 10032.66513491,
                 6281.53627686, 9986.327508 , 8381.51701951, 10371.14255313])
In [24]: from sklearn.metrics import r2 score
In [25]: | r2_score(y test,ypred)
Out[25]: 0.8415526986865394
In [26]: from sklearn.metrics import mean squared error
In [27]: mean squared error(ypred,y test)
Out[27]: 581887.727391353
In [28]: n = 581887.727391353 ** (1/2)
         print(n)
       762.8156575420782
In [29]: #!pip3 install scikit-learn
In [30]: 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)
         GridSearchCV
Out[30]:
          ▶ estimator: Ridge
               ► Ridge
```

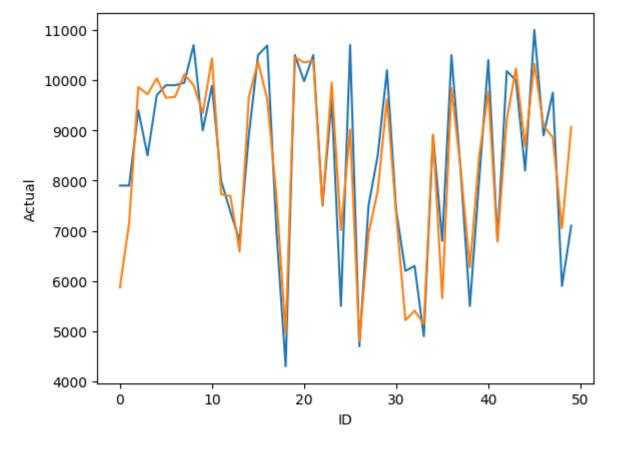
```
In [31]: ridge regressor.best params
Out[31]: {'alpha': 30}
In [32]: ridge = Ridge(alpha=30)
         ridge.fit(x train,y train)
         y pred ridge=ridge.predict(x test)
In [33]: from sklearn.metrics import mean squared error
         Ridge Error = mean squared error(y pred ridge,y test)
         Ridge Error
Out[33]: 579521.7970897449
In [34]: from sklearn.metrics import r2 score
         r2 score(y test,y pred ridge)
Out[34]: 0.8421969385523054
In [35]: import seaborn as sns
         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)
```

```
index Actual
                            Predicted ID
Out[35]:
             481
                   7900
                          5869.741155 0
         0
                   7900
                          7149.563327 1
               76
         2
             1502
                          9862.785355 2
                   9400
             669
                   8500
                          9719.283532 3
            1409
                   9700 10035.895686 4
            1414
                   9900
                          9650.311090 5
            1089
                   9900
                          9669.183317 6
         7 1507
                   9950 10115.128380 7
             970
                  10700
                          9900.241944 8
         9 1198
                   8999
                          9347.080772 9
In [36]: import matplotlib.pyplot as plt
         sns.lineplot(x='ID',y='Actual',data=Results.head(50))
```

plt.plot()

Out[36]: []

sns.lineplot(x='ID',y='Predicted',data=Results.head(50))



In []: