```
import pandas as pd
In [1]:
          import pickle
In [2]: data=pd.read csv("/home/palacement/Downloads/fiat500.csv")
In [3]: data.describe()
Out[3]:
                                             age_in_days
                           ID engine power
                                                                    km previous owners
                                                                                                  lat
                                                                                                              lon
                                                                                                                           price
                                                                                         1538.000000
                  1538.000000
                                 1538.000000
                                             1538.000000
                                                            1538.000000
                                                                             1538.000000
                                                                                                      1538.000000
                                                                                                                    1538.000000
            count
                   769.500000
                                                           53396.011704
                                                                                                         11.563428
            mean
                                   51.904421
                                             1650.980494
                                                                                1.123537
                                                                                            43.541361
                                                                                                                    8576.003901
                                                                                                         2.328190
              std
                   444.126671
                                    3.988023
                                              1289.522278
                                                           40046.830723
                                                                                0.416423
                                                                                             2.133518
                                                                                                                    1939.958641
                     1.000000
                                   51.000000
                                               366.000000
                                                            1232.000000
                                                                                1.000000
                                                                                            36.855839
                                                                                                         7.245400
                                                                                                                    2500.000000
             min
                                                                                                         9.505090
             25%
                   385.250000
                                   51.000000
                                               670.000000
                                                           20006.250000
                                                                                1.000000
                                                                                            41.802990
                                                                                                                    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
                                                                                1.000000
                                                                                            45.467960
                                                                                                         12.769040
                                                           79667.750000
                                                                                                                  10000.000000
             max 1538.000000
                                   77.000000
                                              4658.000000 235000.000000
                                                                                4.000000
                                                                                            46.795612
                                                                                                         18.365520
                                                                                                                  11100.000000
```

In [4]: | data1=data.drop(['ID','lat','lon'],axis=1)

In [5]: data

Out[5]:

	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 [6]: data2=pd.get_dummies(data)
In [7]: data1.shape
Out[7]: (1538, 6)
In [8]: data2=pd.get_dummies(data2)
In [9]: data2.shape
Out[9]: (1538, 11)
```

```
In [10]: y=data2['price']
In [11]: x=data2.drop('price',axis=1)
In [12]: y
Out[12]: 0
                 8900
                 8800
                 4200
         2
                 6000
         3
         4
                 5700
                  . . .
         1533
                 5200
         1534
                 4600
         1535
                 7500
         1536
                 5990
         1537
                 7900
         Name: price, Length: 1538, dtype: int64
```

In [13]: x

Out[13]:

	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 [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)

Out[15]:

		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
1	502	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
1	409	1410	51	762	18800	1	45.538689	9.928310	1	0	0

```
In [16]: x train.shape
Out[16]: (1030, 10)
In [17]: 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 [18]: x_test.head(5)
Out[18]:
                  ID engine_power age_in_days
                                                km previous owners
                                                                         lat
                                                                                 Ion model_lounge model_pop model_sport
                                                                2 40.174702 18.167629
                 482
                                        3197 120000
                                                                                               0
                                                                                                          1
                                                                                                                     0
            481
                               51
                                             103000
                                                                1 45.797859
             76
                  77
                               62
                                                                             8.644440
                                                                                               0
                                                                                                          1
                                                                                                                     0
                                        2101
           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
                                                                1 45.538689
                                                                             9.928310
                                                                                                          0
                                                                                                                     0
           1409 1410
                               51
                                              18800
                                                                                               1
                                         762
In [19]:
          dat1=data.drop('lat',axis=1)
          dat1.shape
In [20]:
Out[20]: (1538, 8)
```

```
In [21]: y_train
Out[21]: 527
                  9990
         129
                  9500
         602
                  7590
                  8750
         331
         323
                  9100
         1130
                 10990
         1294
                  9800
         860
                  5500
         1459
                  9990
         1126
                  8900
         Name: price, Length: 1030, dtype: int64
In [22]: from sklearn.linear model import LinearRegression
         reg=LinearRegression ()
         reg.fit (x_train,y_train)
Out[22]:
          ▼ LinearRegression
          LinearRegression()
In [ ]:
In [23]: ypred=reg.predict(x_test)
```

```
In [24]: | ypred
                                  5343.40955708,
                 10371.21600688.
                                                   9793.46202119. 10248.73590685.
                 10350.88894338.
                                  9418.6649538 .
                                                   9246.75432375.
                                                                   9726.77158038.
                  5646.60360194,
                                                                   9667.14070802,
                                  4954.59993355,
                                                   4854.00609399,
                  6106.03185061,
                                  9895.4585107 , 10067.23023087,
                                                                   4939.52480184,
                  8024.89878537,
                                  9702.49506011,
                                                   5897.90997934, 10144.6495611
                                  9622.44225965, 10171.86736173, 10103.58498957,
                  5395.93461448,
                                                   5809.10532945,
                  9481.19877071,
                                  4918.69676305,
                                                                   7076.07274648,
                 10066.02424638, 10430.97776811, 10050.79995384,
                                                                   7801.53792597,
                  8738.32379912,
                                                                   9856.67153089,
                                  9963.07184541, 10250.69391036,
                  8383.84152492,
                                  9307.84587539,
                                                   8530.90168144,
                                                                   9859.23075392,
                  9733.54483496,
                                  9744.86150125,
                                                   6741.410463
                                                                   7342.18893371,
                  8772.20704958,
                                  9959.77345301,
                                                   9692.26944677, 10524.54487623,
                  8221.41396472,
                                  6722.97284178,
                                                   9894.93188478,
                                                                   8849.71168914,
                  9786.53980838, 10262.59139607, 10382.67498044,
                                                                   9988.41681508,
                  9336.80741819,
                                  9902.52039123,
                                                   9109.63147621, 10147.01866123,
                                  6059.56493387,
                                                   8827.96184211, 10302.33416028,
                  7831.00036415,
                                 10068.83508852,
                  5660.1705204 ,
                                                   9595.70115109,
                                                                   7698.86996869,
                  9319.54039166,
                                  7421.93077111, 10397.65812756, 10008.49656229,
                                                                   6328.88724858
                                                   9995.86970892.
                 10572.26845119,
                                  9890.79746015.
In [25]: from sklearn.metrics import r2 score
         r2_score(y test,ypred)
Out[25]: 0.8428319728488683
In [26]: from sklearn.metrics import mean squared error
         mean squared error(ypred,y test)
Out[26]: 577189.6736608233
```

localhost:8888/notebooks/Untitled2.ipynb

```
In [27]: 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/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
         Ill-conditioned matrix (rcond=9.5143e-26): result may not be accurate.
           return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
         /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
         Ill-conditioned matrix (rcond=7.38942e-26): result may not be accurate.
           return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
         /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
         Ill-conditioned matrix (rcond=6.45639e-26): result may not be accurate.
           return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
         /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
         Ill-conditioned matrix (rcond=6.93626e-23): result may not be accurate.
           return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
         /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
         Ill-conditioned matrix (rcond=7.09552e-23): result may not be accurate.
           return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
         /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
         Ill-conditioned matrix (rcond=7.00948e-23): result may not be accurate.
           return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
         /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning:
         Ill-conditioned matrix (rcond=7.57945e-23): result may not be accurate.
           return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
         /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
         Ill-conditioned matrix (rcond=7.22998e-23): result may not be accurate.
           return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
         /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
         Ill-conditioned matrix (rcond=6.92606e-21): result may not be accurate.
           return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
```

```
/home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
Ill-conditioned matrix (rcond=7.09075e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
/home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
Ill-conditioned matrix (rcond=7.01957e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
/home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
Ill-conditioned matrix (rcond=7.57225e-21): result may not be accurate.
  return linalq.solve(A, Xy, assume a="pos", overwrite a=True).T
/home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
Ill-conditioned matrix (rcond=7.23226e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
/home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
Ill-conditioned matrix (rcond=6.92596e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
/home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
Ill-conditioned matrix (rcond=7.09069e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
/home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
Ill-conditioned matrix (rcond=7.01967e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
/home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
Ill-conditioned matrix (rcond=7.57214e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
/home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarning:
Ill-conditioned matrix (rcond=7.23225e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
 GridSearchCV
 ▶ estimator: Ridge
       ▶ Ridge
```

In [28]: from sklearn.model_selection import GridSearchCV
from sklearn.linear model import Ridge

In [29]: alpha = [1e-15, 1e-10, 1e-8, 1e-4, 1e-3,1e-2, 1, 5, 10, 20,30]

Out[27]:

```
In [30]: ridge = Ridge()

In [31]: parameters = {'alpha': alpha}

In [32]: ridge_regressor = GridSearchCV(ridge, parameters)
```

In [33]: ridge regressor.fit(x train, y train) /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarnin q: Ill-conditioned matrix (rcond=9.5143e-26): result may not be accurate. return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarnin q: Ill-conditioned matrix (rcond=7.38942e-26): result may not be accurate. return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarnin q: Ill-conditioned matrix (rcond=6.45639e-26): result may not be accurate. return linalq.solve(A, Xy, assume a="pos", overwrite a=True).T /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarnin q: Ill-conditioned matrix (rcond=6.93626e-23): result may not be accurate. return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarnin q: Ill-conditioned matrix (rcond=7.09552e-23): result may not be accurate. return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarnin g: Ill-conditioned matrix (rcond=7.00948e-23): result may not be accurate. return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarnin q: Ill-conditioned matrix (rcond=7.57945e-23): result may not be accurate. return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarnin g: Ill-conditioned matrix (rcond=7.22998e-23): result may not be accurate. return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarnin g: Ill-conditioned matrix (rcond=6.92606e-21): result may not be accurate. return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarnin g: Ill-conditioned matrix (rcond=7.09075e-21): result may not be accurate. return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarnin q: Ill-conditioned matrix (rcond=7.01957e-21): result may not be accurate. return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarnin q: Ill-conditioned matrix (rcond=7.57225e-21): result may not be accurate. return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarnin q: Ill-conditioned matrix (rcond=7.23226e-21): result may not be accurate.

return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T

```
Untitled2 - Jupyter Notebook
         /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarnin
         q: Ill-conditioned matrix (rcond=6.92596e-17): result may not be accurate.
           return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
         /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarnin
         q: Ill-conditioned matrix (rcond=7.09069e-17): result may not be accurate.
           return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
         /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarnin
         q: Ill-conditioned matrix (rcond=7.01967e-17): result may not be accurate.
           return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
         /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarnin
         q: Ill-conditioned matrix (rcond=7.57214e-17): result may not be accurate.
           return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
         /home/palacement/anaconda3/lib/python3.10/site-packages/sklearn/linear model/ ridge.py:216: LinAlgWarnin
         q: Ill-conditioned matrix (rcond=7.23225e-17): result may not be accurate.
           return linalg.solve(A, Xy, assume a="pos", overwrite_a=True).T
Out[33]:
            GridSearchCV
          ▶ estimator: Ridge
                ▶ Ridge
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)
```

localhost:8888/notebooks/Untitled2.ipynb

Ridge Error

Out[36]: 574728.5696156605

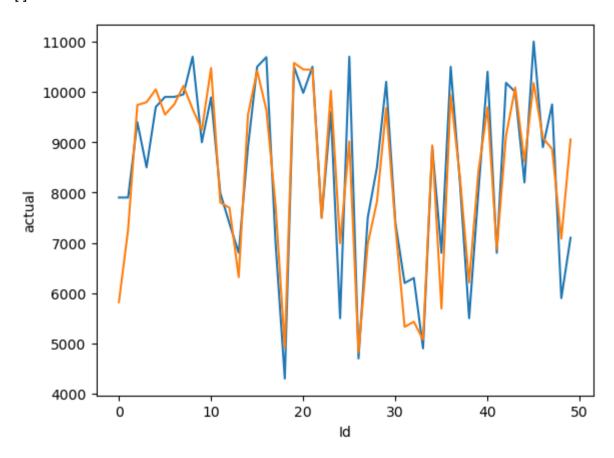
In [36]: **from** sklearn.metrics **import** mean squared error

Ridge Error=mean squared error(y pred ridge,y test)

```
In [37]: from sklearn.metrics import r2 score
          r2 score(y test,y pred ridge)
Out[37]: 0.8435021284061197
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]:
                            predicted Id
             index actual
           0
               481
                    7900
                          5819.298540 0
                76
                    7900
                          7264.574918 1
              1502
                          9738.882706 2
                    9400
               669
                    8500
                          9794.478395 3
              1409
                        10050.350724 4
                    9700
             1414
                    9900
                          9548.821263 5
              1089
                    9900
                          9750.202837 6
              1507
                    9950
                         10118.769447 7
                   10700
                          9656.236315 8
               970
              1198
                    8999
                          9247.205270 9
In [39]: import seaborn as sns
          import matplotlib.pyplot as plt
```

```
In [40]: sns.lineplot(x='Id',y='actual',data=Results.head(50))
sns.lineplot(x='Id',y='predicted',data=Results.head(50))
plt.plot()
```

Out[40]: []



```
In [41]: import pandas as a
         import pickle
         import warnings
         warnings.filterwarnings('ignore')
         from sklearn.model selection import GridSearchCV
In [42]: from sklearn.linear model import ElasticNet
         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
                ▶ ElasticNet
In [43]: elastic regressor.best params
Out[43]: {'alpha': 0.01}
In [44]: elastic=ElasticNet(alpha=0.1)
         elastic.fit(x train,y train)
         y pred elastic=elastic.predict(x test)
In [45]: from sklearn.metrics import mean squared error
         Elastic Error=mean squared error(y pred elastic,y test)
         Elastic Error
Out[45]: 573512.0849841419
```

```
In [46]: from sklearn.metrics import r2_score
    r2_score(y_test,y_pred_elastic)

Out[46]: 0.843833375651731

In [48]: Results=pd.DataFrame(columns=['actual','predicted'])
    Results['actual']=y_test
    Results['predicted']=y_pred_ridge
    import seaborn as sns
    import matplotlib.pyplot as pltd_elastic
    Results=Results.reset_index()
    Results['Id']=Results.index
    Results.head(10)
```

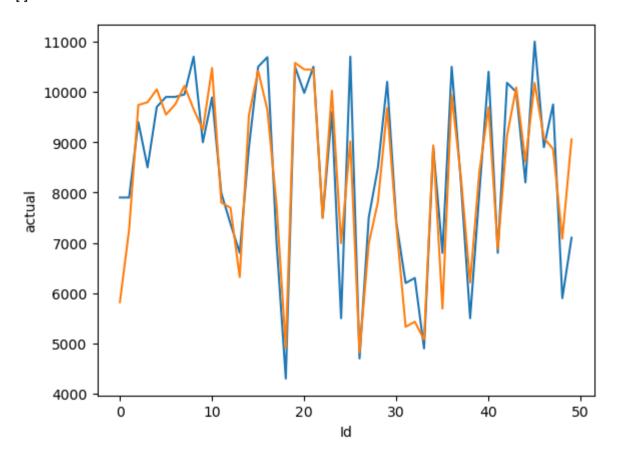
Out[48]:

	index	actual	predicted	ld
0	481	7900	5819.298540	0
1	76	7900	7264.574918	1
2	1502	9400	9738.882706	2
3	669	8500	9794.478395	3
4	1409	9700	10050.350724	4
5	1414	9900	9548.821263	5
6	1089	9900	9750.202837	6
7	1507	9950	10118.769447	7
8	970	10700	9656.236315	8
9	1198	8999	9247.205270	9

```
In [49]: import seaborn as sns
import matplotlib.pyplot as plt
```

```
In [50]: sns.lineplot(x='Id',y='actual',data=Results.head(50))
sns.lineplot(x='Id',y='predicted',data=Results.head(50))
plt.plot()
```

Out[50]: []



In []: