

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

```
In [2]: drug=pd.read_csv(r"C:\Users\reshma_koduri\Downloads\drug_discovery.csv")
drug
```

```
Out[2]:
```

	id	gen	smile	source	score	P_value	Conn
0	AAAA	0	COc1cccc(NC(=O)Cc2ccc(NC(=O)N3CCCC3)cc2)c1	generated	99.9	0.003320	-0
1	AAAB	0	C=CCNC(=O)CNc1cccc(C(=O)N(C)CCc2ccccc2)c1	generated	99.9	0.003384	-0
2	AAAC	0	CC(=O)Nc1ccc(S(=O)(=O)Nc2ccc(C)c(C)c2)cc1	training	99.9	0.003397	-0
3	AAAD	0	CCOC(=O)C1=C(C(=O)OCC)C(c2cccc(Cl)c2)NC(=O)N1	generated	99.9	0.003427	-0
4	AAAE	0	NC(=O)c1ccc(NC(=O)C(CC(=O)O)NC(=O)c2cc(-c3cccc...	generated	99.9	0.003468	-0
...
1172	ABTC	0	CCCC1(CCc2ccccc2)CC(O)=C(C(CC)c2cccc(NS(=O)=O...	manual	99.9	1.000000	0
1173	ABTD	0	O=C1Nc2ccc(Cl)cc2C(C#CC2CC2)(C(F)(F)F)O1	manual	99.9	1.000000	0
1174	ABTE	0	CC(C)(C)NC(=O)C1CN(Cc2cccn2)CCN1CC(O)CC(Cc1cc...	manual	99.9	1.000000	0
1175	ABTF	0	CCOP(=O)(COc1ccc(CC(NC(=O)OC2COC3OCCCC23)C(O)CN...	manual	99.9	1.000000	0
1176	ABTG	0	COC(=O)NC(C(=O)NCCCC(CO)N(CC(C)C)S(=O)(=O)c1c...	manual	99.9	1.000000	0

1177 rows × 8 columns



```
In [3]: drug.describe()
```

```
Out[3]:
```

	gen	score	P_value	Connectivity
count	1177.0	1.177000e+03	1177.000000	1177.000000
mean	0.0	9.990000e+01	0.677346	-0.049811
std	0.0	2.004582e-12	0.392285	0.163636
min	0.0	9.990000e+01	0.003320	-0.809330
25%	0.0	9.990000e+01	0.257861	-0.209375
50%	0.0	9.990000e+01	1.000000	0.000000
75%	0.0	9.990000e+01	1.000000	0.000000
max	0.0	9.990000e+01	1.000000	0.723920

In [4]:

`drug.info()`

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1177 entries, 0 to 1176
Data columns (total 8 columns):
#   Column          Non-Null Count  Dtype
---  -
0   id              1177 non-null   object
1   gen             1177 non-null   int64
2   smile          1177 non-null   object
3   source         1177 non-null   object
4   score          1177 non-null   float64
5   P_value        1177 non-null   float64
6   Connectivity    1177 non-null   float64
7   name           1177 non-null   object
dtypes: float64(3), int64(1), object(4)
memory usage: 73.7+ KB
```

In [7]:

`drug['P_value'].unique()`

Out[7]:

```
array([0.00331968, 0.00338356, 0.00339726, 0.00342658, 0.0034682 ,
       0.00353087, 0.00355484, 0.00357524, 0.00358432, 0.00363285,
       0.0037343 , 0.00389023, 0.00396885, 0.0042186 , 0.00450414,
       0.00486791, 0.00550357, 0.00628477, 0.00643704, 0.00645932,
       0.00664478, 0.00697121, 0.00697142, 0.00757783, 0.00895931,
       0.00914021, 0.00915257, 0.00949567, 0.00980125, 0.01052681,
       0.01165854, 0.01199205, 0.01328552, 0.01357921, 0.01416115,
       0.01450921, 0.01463088, 0.01463118, 0.01520905, 0.01579844,
       0.01631903, 0.01670527, 0.01700551, 0.01744755, 0.01788815,
       0.01826373, 0.0196488 , 0.01981558, 0.02005149, 0.02089379,
       0.02101087, 0.02143682, 0.02161217, 0.0219501 , 0.02234632,
       0.02278351, 0.02366028, 0.023799 , 0.02386443, 0.02525801,
       0.02753619, 0.02795078, 0.02799259, 0.02833159, 0.02851516,
       0.02862323, 0.0286239 , 0.0289735 , 0.03181352, 0.03252018,
       0.03329107, 0.03354188, 0.03489295, 0.03526253, 0.03633253,
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       0.04676691, 0.04695373, 0.04730705, 0.04757408, 0.04768286,
       0.04870295, 0.05051713, 0.05053752, 0.05088461, 0.05182202,
       0.05275996, 0.05312042, 0.05427295, 0.05438078, 0.05514716,
       0.0552889 , 0.05568718, 0.05570817, 0.05605124, 0.05631784,
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       0.06946658, 0.06976797, 0.06985624, 0.0704378 , 0.07101772,
       0.0715195 , 0.07235723, 0.07247133, 0.07256171, 0.07294612,
       0.07348202, 0.07354344, 0.07386633, 0.07582825, 0.07832784,
       0.07905461, 0.07907366, 0.07934654, 0.07973238, 0.07980567,
       0.07985288, 0.08081229, 0.08163699, 0.08181505, 0.08269558,
       0.08323564, 0.08490506, 0.08534807, 0.08605934, 0.08635457,
       0.08788697, 0.08806246, 0.08879437, 0.08895638, 0.09034253,
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       0.09238933, 0.09306361, 0.09512018, 0.09555039, 0.09599071,
       0.09605064, 0.09713684, 0.0985899 , 0.09952477, 0.10055522,
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       0.12540111, 0.12793708, 0.12933567, 0.12954606, 0.12988079,
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0.89319651, 0.89734209, 0.89865245, 0.9007128 , 0.90102661,
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0.94673358, 0.95926652, 0.96551891, 0.96554576, 0.96982546,
0.97057751, 0.97200691, 0.97305079, 0.97315653, 0.97444229,
0.97716526, 0.98104994, 0.98491947, 0.99460722, 0.99893939,
1.      ])
```

```
In [8]: drug['source'].unique()
```

```
Out[8]: array(['generated', 'training', 'hiv', 'manual'], dtype=object)
```

```
In [9]: drug['gen'].unique()
```

```
Out[9]: array([0], dtype=int64)
```

```
In [10]: drug_sorted = drug.sort_values(by = 'P_value', ascending = True)
drug_sorted
```

```
Out[10]:
```

	id	gen	smile	source	score	P_value	C
0	AAAA	0	COc1cccc(NC(=O)Cc2ccc(NC(=O)N3CCCC3)cc2)c1	generated	99.9	0.003320	
1	AAAB	0	C=CCNC(=O)CNc1cccc(C(=O)N(C)CCc2ccccc2)c1	generated	99.9	0.003384	
2	AAAC	0	CC(=O)Nc1ccc(S(=O)(=O)Nc2ccc(C)c(C)c2)cc1	training	99.9	0.003397	
3	AAAD	0	CCOC(=O)C1=C(C(=O)OCC)C(c2cccc(Cl)c2)NC(=O)N1	generated	99.9	0.003427	
4	AAAE	0	NC(=O)c1ccc(NC(=O)C(CC(=O)O)NC(=O)c2cc(-c3cccc...	generated	99.9	0.003468	
...
772	ABDS	0	COc1ccc2c(c1)OC(CNC(=O)NCc1ccco1)CC2	generated	99.9	1.000000	
773	ABDT	0	COC(=O)C1COC(=O)N(c2ccc(NS(C)(=O)=O)cc2)C1	generated	99.9	1.000000	
774	ABDU	0	O=C(COc1ccc2cc(OCCCN3CCOCC3)ccc2c1)NCC(c1ccccc...	generated	99.9	1.000000	
767	ABDN	0	Cc1cccc(C)c1N(C)S(=O)(=O)c1cnn(C)c1	generated	99.9	1.000000	
1176	ABTG	0	COC(=O)NC(C(=O)NCCCC(CO)N(CC(C)C)S(=O)(=O)c1c...	manual	99.9	1.000000	

1177 rows × 8 columns



```
In [11]: drug_sorted = drug_sorted[['smile', 'P_value']]
drug_sorted
```

```
Out[11]:
```

	smile	P_value
0	COc1cccc(NC(=O)Cc2ccc(NC(=O)N3CCCC3)cc2)c1	0.003320
1	C=CCNC(=O)CNc1cccc(C(=O)N(C)CCc2ccccc2)c1	0.003384
2	CC(=O)Nc1ccc(S(=O)(=O)Nc2ccc(C)c(C)c2)cc1	0.003397
3	CCOC(=O)C1=C(C(=O)OCC)C(c2cccc(Cl)c2)NC(=O)N1	0.003427

	smile	P_value
4	<chem>NC(=O)c1ccc(NC(=O)C(CC(=O)O)NC(=O)c2cc(-c3cccc...</chem>	0.003468
...
772	<chem>COc1ccc2c(c1)OC(CNC(=O)NCc1ccco1)CC2</chem>	1.000000
773	<chem>COC(=O)C1COC(=O)N(c2ccc(NS(C)(=O)=O)cc2)C1</chem>	1.000000
774	<chem>O=C(COc1ccc2cc(OCCCN3CCOCC3)ccc2c1)NCC(c1cccc...</chem>	1.000000
767	<chem>Cc1cccc(C)c1N(C)S(=O)(=O)c1cnn(C)c1</chem>	1.000000
1176	<chem>COC(=O)NC(C(=O)NCCCC(CO)N(CC(C)C)S(=O)(=O)c1c...</chem>	1.000000

1177 rows × 2 columns

In [12]:

```
drug_sorted.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1177 entries, 0 to 1176
Data columns (total 2 columns):
#   Column   Non-Null Count  Dtype
---  -
0    smile   1177 non-null   object
1    P_value  1177 non-null   float64
dtypes: float64(1), object(1)
memory usage: 27.6+ KB
```

In [13]:

```
drug['source']=drug['source'].map({'generated':1,'training':0,'hiv':2,'manual':3})
```

In [14]:

```
drug
```

Out[14]:

	id	gen	smile	source	score	P_value	Connect
0	AAAA	0	<chem>COc1cccc(NC(=O)Cc2ccc(NC(=O)N3CCCC3)cc2)c1</chem>	1	99.9	0.003320	-0.370
1	AAAB	0	<chem>C=CCNC(=O)CNc1cccc(C(=O)N(C)CCc2ccccc2)c1</chem>	1	99.9	0.003384	-0.260
2	AAAC	0	<chem>CC(=O)Nc1ccc(S(=O)(=O)Nc2ccc(C)c(C)c2)cc1</chem>	0	99.9	0.003397	-0.310
3	AAAD	0	<chem>CCOC(=O)C1=C(C(=O)OCC)C(c2cccc(Cl)c2)NC(=O)N1</chem>	1	99.9	0.003427	-0.320
4	AAAE	0	<chem>NC(=O)c1ccc(NC(=O)C(CC(=O)O)NC(=O)c2cc(-c3cccc...</chem>	1	99.9	0.003468	-0.280
...
1172	ABTC	0	<chem>CCCC1(CCc2ccccc2)CC(O)=C(C(C)C)c2cccc(NS(=O)=O...</chem>	3	99.9	1.000000	0.000
1173	ABTD	0	<chem>O=C1Nc2ccc(Cl)cc2C(C#CC2CC2)(C(F)(F)F)O1</chem>	3	99.9	1.000000	0.000
1174	ABTE	0	<chem>CC(C)(C)NC(=O)C1CN(Cc2cccn2)CCN1CC(O)CC(Cc1cc...</chem>	3	99.9	1.000000	0.000
1175	ABTF	0	<chem>CCOP(=O)(COc1ccc(CC(NC(=O)OC2COC3OCCCC23)C(O)CN...</chem>	3	99.9	1.000000	0.000
1176	ABTG	0	<chem>COC(=O)NC(C(=O)NCCCC(CO)N(CC(C)C)S(=O)(=O)c1c...</chem>	3	99.9	1.000000	0.000

1177 rows × 8 columns

```
In [15]: drug1=drug.drop(['id','gen','name'],axis=1)
drug1
```

```
Out[15]:
```

	smile	source	score	P_value	Connectivity
0	<chem>COc1cccc(NC(=O)Cc2ccc(NC(=O)N3CCCC3)cc2)c1</chem>	1	99.9	0.003320	-0.376625
1	<chem>C=CCNC(=O)CNc1cccc(C(=O)N(C)CCc2ccccc2)c1</chem>	1	99.9	0.003384	-0.269090
2	<chem>CC(=O)Nc1ccc(S(=O)(=O)Nc2ccc(C)c(C)c2)cc1</chem>	0	99.9	0.003397	-0.318895
3	<chem>CCOC(=O)C1=C(C(=O)OCC)C(c2cccc(Cl)c2)NC(=O)N1</chem>	1	99.9	0.003427	-0.329905
4	<chem>NC(=O)c1ccc(NC(=O)C(CC(=O)O)NC(=O)c2cc(-c3cccc...</chem>	1	99.9	0.003468	-0.288555
...
1172	<chem>CCCC1(CCc2ccccc2)CC(O)=C(C(CC)c2cccc(NS(=O)(=O...</chem>	3	99.9	1.000000	0.000000
1173	<chem>O=C1Nc2ccc(Cl)cc2C(C#CC2CC2)(C(F)(F)F)O1</chem>	3	99.9	1.000000	0.000000
1174	<chem>CC(C)(C)NC(=O)C1CN(Cc2ccnc2)CCN1CC(O)CC(Cc1cc...</chem>	3	99.9	1.000000	0.000000
1175	<chem>CCOP(=O)(COc1ccc(CC(NC(=O)OC2COC3OCCC23)C(O)CN...</chem>	3	99.9	1.000000	0.000000
1176	<chem>COC(=O)NC(C(=O)NCCCC(CO)N(CC(C)C)S(=O)(=O)c1c...</chem>	3	99.9	1.000000	0.000000

1177 rows × 5 columns

```
In [17]: drug1
```

```
Out[17]:
```

	smile	source	score	P_value	Connectivity
0	<chem>COc1cccc(NC(=O)Cc2ccc(NC(=O)N3CCCC3)cc2)c1</chem>	1	99.9	0.003320	-0.376625
1	<chem>C=CCNC(=O)CNc1cccc(C(=O)N(C)CCc2ccccc2)c1</chem>	1	99.9	0.003384	-0.269090
2	<chem>CC(=O)Nc1ccc(S(=O)(=O)Nc2ccc(C)c(C)c2)cc1</chem>	0	99.9	0.003397	-0.318895
3	<chem>CCOC(=O)C1=C(C(=O)OCC)C(c2cccc(Cl)c2)NC(=O)N1</chem>	1	99.9	0.003427	-0.329905
4	<chem>NC(=O)c1ccc(NC(=O)C(CC(=O)O)NC(=O)c2cc(-c3cccc...</chem>	1	99.9	0.003468	-0.288555
...
1172	<chem>CCCC1(CCc2ccccc2)CC(O)=C(C(CC)c2cccc(NS(=O)(=O...</chem>	3	99.9	1.000000	0.000000
1173	<chem>O=C1Nc2ccc(Cl)cc2C(C#CC2CC2)(C(F)(F)F)O1</chem>	3	99.9	1.000000	0.000000
1174	<chem>CC(C)(C)NC(=O)C1CN(Cc2ccnc2)CCN1CC(O)CC(Cc1cc...</chem>	3	99.9	1.000000	0.000000
1175	<chem>CCOP(=O)(COc1ccc(CC(NC(=O)OC2COC3OCCC23)C(O)CN...</chem>	3	99.9	1.000000	0.000000
1176	<chem>COC(=O)NC(C(=O)NCCCC(CO)N(CC(C)C)S(=O)(=O)c1c...</chem>	3	99.9	1.000000	0.000000

1177 rows × 5 columns

```
In [18]: drug1.isna().sum()
```

```
Out[18]: smile      0
source      0
score       0
P_value     0
Connectivity 0
dtype: int64
```

```
In [23]: x=drug1.drop(['smile', 'P_value'],axis=1)
y=drug1['P_value']
```

```
In [24]: x
```

```
Out[24]:
```

	source	score	Connectivity
0	1	99.9	-0.376625
1	1	99.9	-0.269090
2	0	99.9	-0.318895
3	1	99.9	-0.329905
4	1	99.9	-0.288555
...
1172	3	99.9	0.000000
1173	3	99.9	0.000000
1174	3	99.9	0.000000
1175	3	99.9	0.000000
1176	3	99.9	0.000000

1177 rows × 3 columns

```
In [25]: y
```

```
Out[25]: 0      0.003320
1      0.003384
2      0.003397
3      0.003427
4      0.003468
...
1172    1.000000
1173    1.000000
1174    1.000000
1175    1.000000
1176    1.000000
Name: P_value, Length: 1177, dtype: float64
```

```
In [26]: from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.30,random_state=42)
```

```
In [51]: from sklearn.linear_model import LinearRegression
regressor=LinearRegression()
regressor.fit(x_train, y_train)
```

Out[51]: ▾ LinearRegression

LinearRegression()

In [54]:
y_pred1=regressor.predict(x_test)
y_pred1

Out[54]: array([0.4792085 , 0.73645914, 0.44729332, 0.73645914, 0.73645914,
0.73645914, 0.73645914, 0.73645914, 0.47052954, 0.54183498,
0.46870273, 0.50462075, 0.73645914, 0.73645914, 0.46724534,
0.96909842, 0.56132863, 0.73645914, 0.98740331, 0.73645914,
0.38314728, 0.51886069, 0.51886572, 0.73645914, 0.42158891,
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0.45530233, 0.73645914, 0.73645914, 0.44926283, 0.46404339,
0.73645914, 0.73645914, 0.54334108, 0.50082277, 0.73645914,
0.73645914, 0.57090419, 0.95277312, 0.64107794, 0.73645914,
0.51679043, 0.73645914, 0.73645914, 0.73645914, 0.53255157,
0.64107794, 0.49644551, 0.5045452 , 0.98257271, 0.73645914,
0.73645914, 0.73645914, 0.73645914, 0.83184034, 0.73645914,
0.73645914, 0.73645914, 0.52508656, 0.73645914, 0.73645914,
0.73645914, 0.73645914, 0.91823361, 0.73645914, 0.84751917,
0.92460556, 0.73645914, 0.73645914, 0.46433389, 0.73645914,
0.73645914, 0.51671487, 0.51224191, 0.73645914, 0.73645914,
0.99499425, 0.94534338, 0.48778671, 0.94969041, 0.9707103 ,
0.51177346, 0.40662025, 0.73645914, 0.73645914, 0.73645914,
0.94381209, 0.73645914, 0.73645914, 0.73645914, 0.73645914,
0.52552983, 0.54759744, 0.96161327, 0.73645914, 0.73645914,
0.73645914, 0.43915837, 0.73645914, 0.73645914, 0.73645914,
0.45683866, 0.73645914, 0.46081798, 0.73645914, 0.73645914,
0.94979619, 0.40853773, 0.92722154, 0.51685088, 0.73645914,
0.94446188, 0.54730025, 0.52515205, 0.73645914, 0.51154679,
0.73645914, 0.73645914, 0.48728803, 0.96581926, 0.93918298,
0.49885325, 0.96139163, 0.47794418, 0.73645914, 0.92703345,
0.48527319, 0.73645914, 0.73645914, 0.54621224, 0.9807795 ,
0.73645914, 0.73645914, 0.56129337, 0.48520267, 0.47579333,
0.47254943, 0.73645914, 0.52556509, 0.88306611, 0.73645914,
0.450779 , 0.73645914, 1.0587289 , 0.73645914, 0.73645914,
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0.83184034, 0.46947678, 0.73645914, 0.64107794, 0.73645914,
0.73645914, 0.73645914, 0.73645914, 0.49485882, 0.55462422,
0.73645914, 0.73645914, 0.73645914, 0.73645914, 0.41264802,
0.44922923, 0.92722154, 0.73645914, -0.07887897, 0.73645914,
0.73645914, 0.73645914, 0.73645914, 0.73645914, 0.73645914,
0.93360185, 0.73645914, 0.73645914, 0.90923228, 0.53781536,
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0.55669448, 0.64107794, 1.01191392, 0.73645914, 0.73645914,
0.73645914, 0.73645914, 0.545502 , 0.73645914, 0.54906324,
0.64107794, 0.42048578, 0.73645914, 0.73645914, 0.73645914,
0.50107462, 0.73645914, 0.73645914, 0.52525279, 0.46433892,
0.91042607, 0.73645914, 0.73645914, 0.73645914, 0.54689728,
0.46459582, 0.73645914, 0.3996237 , 0.49422414, 0.73645914,
0.73645914, 0.49246115, 0.95949768, 0.9313553 , 0.54105926,
0.49426948, 0.4651499 , 0.52360565, 0.73645914, 0.50987951,
0.48183787, 0.73645914, 0.41524717, 0.92722154, 0.93672487,
0.73645914, 0.73645914, 1.00077686, 0.53646038, 0.559344 ,
0.93377815, 0.47260483, 0.73645914, 0.94553479, 0.73645914,
1.02893434, 0.73645914, 0.98018512, 0.73645914, 0.99875194,
0.73645914, 0.52377188, 0.97063474, 0.93013128, 1.06892906,
0.73645914, 0.53384611, 0.73645914, 0.47154704, 0.73645914,
0.73645914, 0.50492298, 0.41596244, 0.99759844, 0.95059205,
0.94154539, 0.97490622, 0.73645914, 0.73645914, 0.40410507,
0.53643015, 0.73645914, 0.73645914, 0.73645914, 0.52176207,


```

0.73645914, 0.73645914, 0.73645914, 0.47339566, 0.73645914,
0.73645914, 0.52731801, 0.73645914, 0.56646649, 0.73645914,
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0.4141239 , 0.73645914, 0.73645914, 0.73645914, 0.73645914,
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0.51391927, 0.73645914, 0.44810933, 0.91208329, 0.3198156 ,
0.27815864, 0.50809133, 0.73645914, 0.95625377, 0.73645914,
0.50654493, 0.92920949, 0.43175381, 0.73645914, 0.94555997,
0.52610406, 0.73645914, 0.73645914, 0.47404545, 0.73645914,
0.73645914, 0.73645914, 0.53078354, 0.51814542, 0.42319237,
0.30838134, 0.94641628, 1.01619044, 0.95181607, 1.03537178,
0.45971485, 0.73645914, 0.38081344, 0.49300516, 0.73645914,
0.73645914, 0.73645914, 0.48277981, 0.73645914, 0.73645914,
0.92722154, 0.73645914, 0.73645914, 0.73645914])

```

```

In [55]: from sklearn.metrics import r2_score
         r2_score(y_test,y_pred1)

```

```
Out[55]: 0.07536894330655464
```

```

In [56]: from sklearn.metrics import mean_squared_error
         mean_squared_error(y_test,y_pred1)

```

```
Out[56]: 0.14430117799862377
```

```

In [57]: results=pd.DataFrame(columns=['actual','predicted'])
         results['actual']=y_test
         results['predicted']=y_pred1
         results=results.reset_index()
         results['ID']=results.index
         results.head(5)

```

```
Out[57]:
```

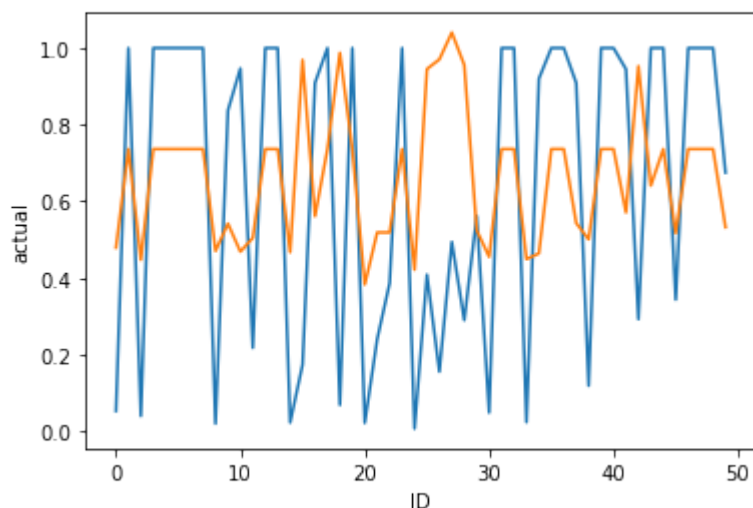
	index	actual	predicted	ID
0	107	0.053120	0.479208	0
1	774	1.000000	0.736459	1
2	81	0.039904	0.447293	2
3	787	1.000000	0.736459	3
4	665	1.000000	0.736459	4

```

In [58]: 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[58]: []
```



```
In [59]: from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestRegressor
reg=RandomForestRegressor()
n_estimators=[25,50,75,100,125,150,175,200]
criterion=['squared_error']
max_depth=[3,5,10]
parameters={'n_estimators': n_estimators,'criterion':criterion,'max_depth':max_depth}
rfc_reg = GridSearchCV(reg, parameters)
rfc_reg.fit(x_train,y_train)
```

```
Out[59]: ▸ GridSearchCV
▸ estimator: RandomForestRegressor
  ▸ RandomForestRegressor
```

```
In [34]: rfc_reg.best_params_
```

```
Out[34]: {'criterion': 'squared_error', 'max_depth': 3, 'n_estimators': 100}
```

```
In [60]: reg=RandomForestRegressor(n_estimators=100,criterion='squared_error',max_depth=3)
```

```
In [61]: reg.fit(x_train,y_train)
```

```
Out[61]: ▾ RandomForestRegressor
RandomForestRegressor(max_depth=3)
```

```
In [63]: y_pred2=reg.predict(x_test)
y_pred2
```

```
Out[63]: array([0.1105979 , 0.98309181, 0.07864243, 0.98309181, 0.98309181,
0.98309181, 0.98309181, 0.98309181, 0.08299423, 0.68306458,
0.9810374 , 0.18038375, 0.98309181, 0.98309181, 0.08213904,
0.2403811 , 0.97888836, 0.98309181, 0.2403811 , 0.98309181,
0.1105979 , 0.37034336, 0.37034336, 0.98309181, 0.07864243,
0.45420826, 0.2403811 , 0.2403811 , 0.24385797, 0.39389183,
0.08213904, 0.98309181, 0.98309181, 0.07864243, 0.97888836,
0.98309181, 0.98309181, 0.68306458, 0.17107253, 0.98309181,
```

0.98309181, 0.98309181, 0.24385797, 0.98309181, 0.98309181,
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0.98309181, 0.98309181, 0.98309181, 0.98309181, 0.98309181,
0.98309181, 0.98309181, 0.39477277, 0.98309181, 0.98309181,
0.98309181, 0.98309181, 0.97623168, 0.98309181, 0.45639779,
0.97623168, 0.98309181, 0.98309181, 0.08213904, 0.98309181,
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0.2403811 , 0.45420826, 0.15384059, 0.31964021, 0.2403811 ,
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0.45639779, 0.98309181, 0.98309181, 0.98309181, 0.98309181,
0.3942879 , 0.68306458, 0.24385797, 0.98309181, 0.98309181,
0.98309181, 0.07864243, 0.98309181, 0.98309181, 0.98309181,
0.08213904, 0.98309181, 0.08213904, 0.98309181, 0.98309181,
0.31964021, 0.07864243, 0.98309181, 0.34893965, 0.98309181,
0.45639779, 0.68306458, 0.39477277, 0.98309181, 0.23492148,
0.98309181, 0.98309181, 0.15384059, 0.24197299, 0.46376708,
0.16780143, 0.24385797, 0.1105979 , 0.98309181, 0.97623168,
0.15384059, 0.98309181, 0.98309181, 0.68306458, 0.2403811 ,
0.98309181, 0.98309181, 0.97888836, 0.15384059, 0.1105979 ,
0.08649073, 0.98309181, 0.3942879 , 0.2403811 , 0.98309181,
0.07864243, 0.98309181, 0.24505316, 0.98309181, 0.98309181,
0.24385797, 0.16780143, 0.98309181, 0.97354632, 0.15384059,
0.98309181, 0.08213904, 0.98309181, 0.98309181, 0.98309181,
0.98309181, 0.98309181, 0.98309181, 0.15623551, 0.92607113,
0.98309181, 0.98309181, 0.98309181, 0.98309181, 0.07864243,
0.68306458, 0.98309181, 0.98309181, 0.12908683, 0.98309181,
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0.97354632, 0.98309181, 0.2403811 , 0.98309181, 0.98309181,
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0.98309181, 0.07864243, 0.98309181, 0.98309181, 0.98309181,
0.17107253, 0.98309181, 0.98309181, 0.39477277, 0.08213904,
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0.08213904, 0.98309181, 0.15623551, 0.15623551, 0.98309181,
0.98309181, 0.15384059, 0.24385797, 0.92390784, 0.68306458,
0.15623551, 0.08213904, 0.38186201, 0.98309181, 0.18038375,
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0.84597302, 0.0911396 , 0.98309181, 0.45420826, 0.98309181,
0.2403811 , 0.98309181, 0.2403811 , 0.98309181, 0.2403811 ,
0.98309181, 0.39098956, 0.2403811 , 0.95361485, 0.24505316,
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0.45639779, 0.2403811 , 0.98309181, 0.98309181, 0.07864243,
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0.98309181, 0.15384059, 0.98309181, 0.98309181, 0.98309181,
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0.07864243, 0.98309181, 0.98309181, 0.98309181, 0.98309181,
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0.18038375, 0.95361485, 0.07864243, 0.98309181, 0.45420826,
0.3942879 , 0.98309181, 0.98309181, 0.10638875, 0.98309181,
0.98309181, 0.98309181, 0.42831935, 0.37076762, 0.36476196,
0.07864243, 0.45420826, 0.2403811 , 0.24610428, 0.2403811 ,
0.08213904, 0.98309181, 0.11383012, 0.15384059, 0.98309181,
0.98309181, 0.98309181, 0.15384059, 0.98309181, 0.98309181,
0.98309181, 0.98309181, 0.98309181, 0.98309181])

```
In [64]: from sklearn.metrics import r2_score  
r2_score(y_test,y_pred2)
```

```
Out[64]: 0.9381965864950121
```

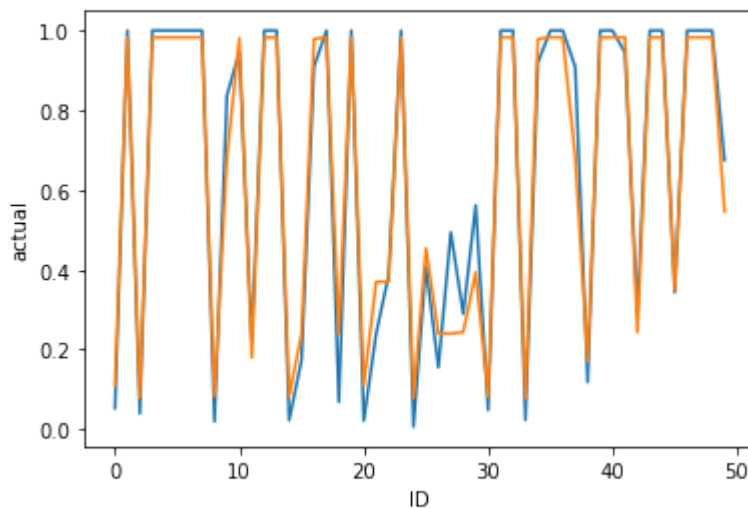
```
In [65]: results=pd.DataFrame(columns=['actual','predicted'])  
results['actual']=y_test  
results['predicted']=y_pred2  
results=results.reset_index()  
results['ID']=results.index  
results.head(5)
```

```
Out[65]:
```

	index	actual	predicted	ID
0	107	0.053120	0.110598	0
1	774	1.000000	0.983092	1
2	81	0.039904	0.078642	2
3	787	1.000000	0.983092	3
4	665	1.000000	0.983092	4

```
In [66]: 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[66]: []
```



```
In [ ]:
```