EX.NO:8 **A PYTHON PROGRAM TO IMPLEMENT**

DATE : 18.10.2024 **GRADIENT BOOSTING**

AIM:-

To implement a python program using the gradient boosting model.

ALGORITHM:-

Step1: Import all the other necessary libraries(numpy as np, matplotlib.pyplot as plt and pandas as pd).

Step2: Generate random numbers from the standard uniform distribution using random.seed().

Step3: Fit a simple decision tree regressor on data [call x as input and y as output].

Step4: Calculate error residuals. Actual target value, minus predicted target value [e1= y - y_predicted1].

Step5: Fit a new model on error residuals as target variable with same input variables [call it e1_predicted].

Step6: Add the predicted residuals to the previous predictions [y_predicted2 = y_predicted1 + e1_predicted].

Step7: Fit another model on residuals that is still left. i.e. [e2 = y - y_predicted2] and repeat steps 2 to 5 until it starts overfitting or the sum of residuals become constant.

Step8: Overfitting can be controlled by consistently checking accuracy on validation data.

Step9: Plot the graph using the “tight_layout” function and the following parameters(h_pad=0.5, w_pad=0.5, pad=2.5).

Step10: Create a function to do gradient boosting where (gradient_boost(X,y,number1,lr,count+1,regs,foo=foo)).

Step11: Plot all the x_label and y_label feature pairs.

IMPLEMENTATION:-

```
import numpy as np import
matplotlib.pyplot as plt import
pandas as pd

np.random.seed(42)
X = np.random.rand(100, 1) - 0.5 y = 3*X[:,
0]**2 + 0.05 * np.random.randn(100)

df = pd.DataFrame()

df['X'] = X.reshape(100) df['y']
= y

df
```

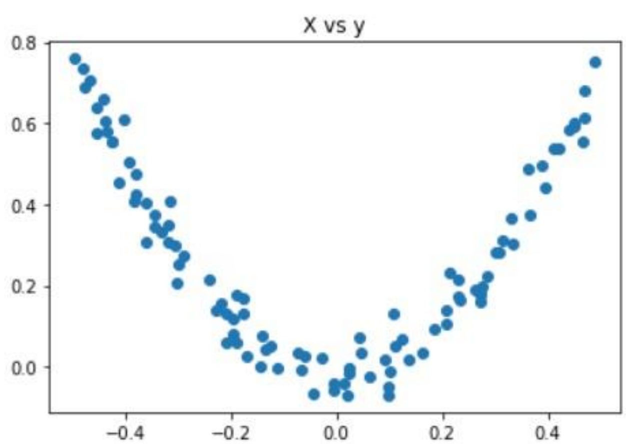
[6]:

	X	y
0	-0.125460	0.051573
1	0.450714	0.594480
2	0.231994	0.166052
3	0.098658	-0.070178
4	-0.343981	0.343986
...	...	...
95	-0.006204	-0.040675
96	0.022733	-0.002305
97	-0.072459	0.032809
98	-0.474581	0.689516
99	-0.392109	0.502607

plt.scatter(df['X'],df['y']) plt.title('X vs y')

Text(0.5, 1.0, 'X vs y')

[9]: Text(0.5, 1.0, 'X vs y')



df['pred1'] = df['y'].mean() df

[11]:

	X	y	pred1
0	-0.125460	0.051573	0.265458
1	0.450714	0.594480	0.265458
2	0.231994	0.166052	0.265458
3	0.098658	-0.070178	0.265458
4	-0.343981	0.343986	0.265458
...	...	...	...
95	-0.006204	-0.040675	0.265458
96	0.022733	-0.002305	0.265458
97	-0.072459	0.032809	0.265458
98	-0.474581	0.689516	0.265458
99	-0.392109	0.502607	0.265458

100 rows × 3 columns

```
df['res1'] = df['y'] - df['pred1']
```

```
df
```

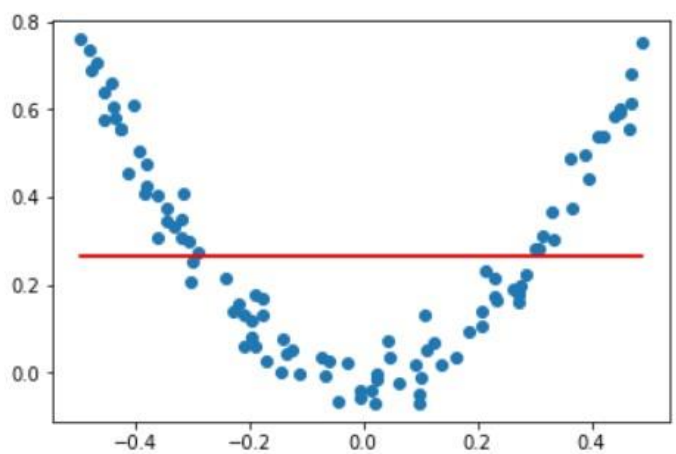
[13]:

	X	y	pred1	res1
0	-0.125460	0.051573	0.265458	-0.213885
1	0.450714	0.594480	0.265458	0.329021
2	0.231994	0.166052	0.265458	-0.099407
3	0.098658	-0.070178	0.265458	-0.335636
4	-0.343981	0.343986	0.265458	0.078528
...	...	...	...	...
95	-0.006204	-0.040675	0.265458	-0.306133
96	0.022733	-0.002305	0.265458	-0.267763
97	-0.072459	0.032809	0.265458	-0.232650
98	-0.474581	0.689516	0.265458	0.424057
99	-0.392109	0.502607	0.265458	0.237148

100 rows × 4 columns

plt.scatter(df['X'],df['y']) plt.plot(df['X'],df['pred1'],color='red')

[14]: [<matplotlib.lines.Line2D at 0x7f6ef51f7a10>]



from sklearn.tree import DecisionTreeRegressor

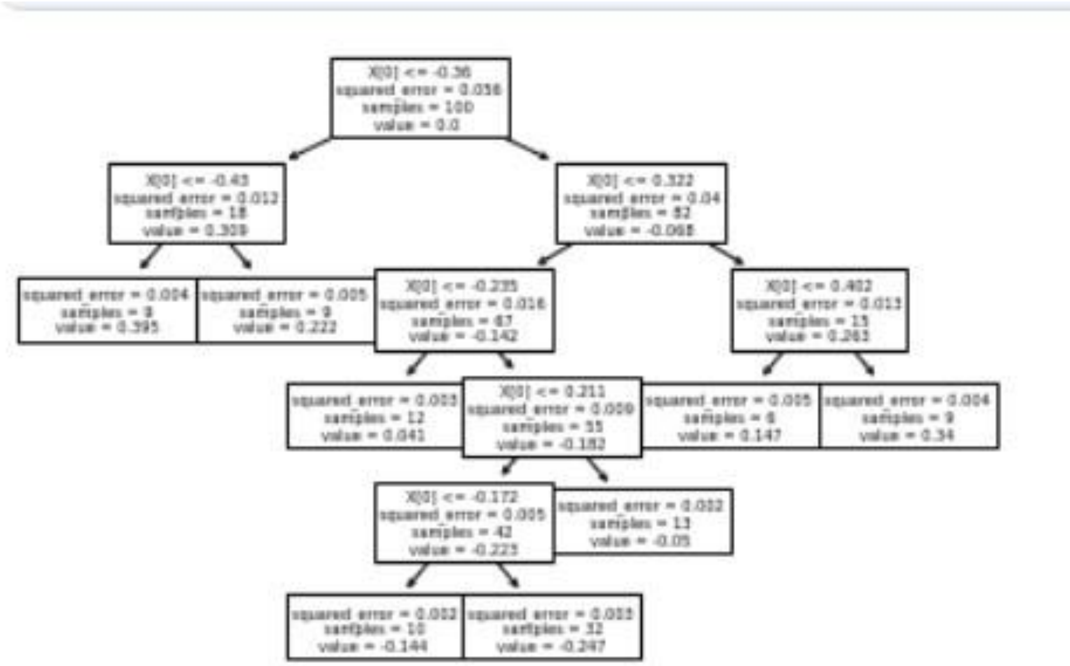
tree1 = DecisionTreeRegressor(max_leaf_nodes=8)

tree1.fit(df['X'].values.reshape(100,1),df['res1'].values)

DecisionTreeRegressor(max_leaf_nodes=8)

from sklearn.tree import plot_tree

plot_tree(tree1) plt.show()



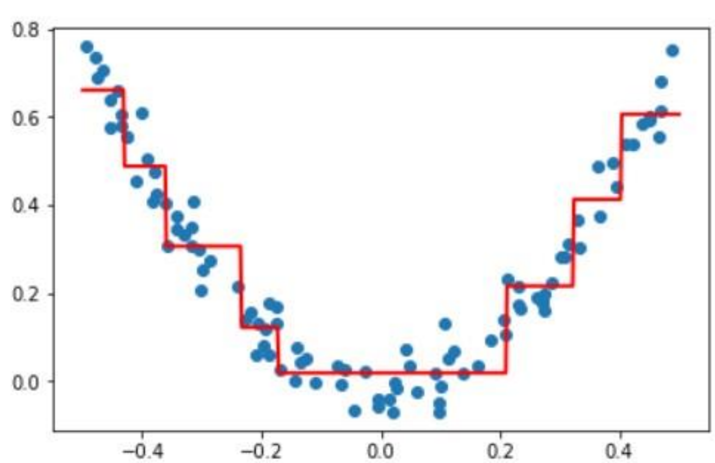
X_test = np.linspace(-0.5, 0.5, 500)

y_pred = 0.265458 + tree1.predict(X_test.reshape(500, 1))

plt.figure(figsize=(14,4)) plt.subplot(121)

plt.plot(X_test, y_pred, linewidth=2,color='red') plt.scatter(df['X'],df['y'])

[21]: <matplotlib.collections.PathCollection at 0x7f6ed205ca50>



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df['pred2'] = **0.265458** + tree1.predict(df['X'].values.reshape(100,1)) df

[92]:

	X	y	pred1	res1	pred2
0	-0.125460	0.051573	0.265458	-0.213885	0.018319
1	0.450714	0.594480	0.265458	0.329021	0.605884
2	0.231994	0.166052	0.265458	-0.099407	0.215784
3	0.098658	-0.070178	0.265458	-0.335636	0.018319
4	-0.343981	0.343986	0.265458	0.078528	0.305964
...	...	...	...	...	...
95	-0.006204	-0.040675	0.265458	-0.306133	0.018319
96	0.022733	-0.002305	0.265458	-0.267763	0.018319
97	-0.072459	0.032809	0.265458	-0.232650	0.018319
98	-0.474581	0.689516	0.265458	0.424057	0.660912
99	-0.392109	0.502607	0.265458	0.237148	0.487796

100 rows × 5 columns

```
df['res2'] = df['y'] - df['pred2']
df
```

[26]:

	X	y	pred1	res1	pred2	res2
0	-0.125460	0.051573	0.265458	-0.213885	0.018319	0.033254
1	0.450714	0.594480	0.265458	0.329021	0.605884	-0.011404
2	0.231994	0.166052	0.265458	-0.099407	0.215784	-0.049732
3	0.098658	-0.070178	0.265458	-0.335636	0.018319	-0.088497
4	-0.343981	0.343986	0.265458	0.078528	0.305964	0.038022
...	...	...	...	...	...	...
95	-0.006204	-0.040675	0.265458	-0.306133	0.018319	-0.058994
96	0.022733	-0.002305	0.265458	-0.267763	0.018319	-0.020624
97	-0.072459	0.032809	0.265458	-0.232650	0.018319	0.014489
98	-0.474581	0.689516	0.265458	0.424057	0.660912	0.028604
99	-0.392109	0.502607	0.265458	0.237148	0.487796	0.014810

100 rows × 6 columns

tree2 = DecisionTreeRegressor(max_leaf_nodes=8)

tree2.fit(df['X'].values.reshape(100,1),df['res2'].values)

DecisionTreeRegressor(max_leaf_nodes=8) y_pred = 0.265458 +

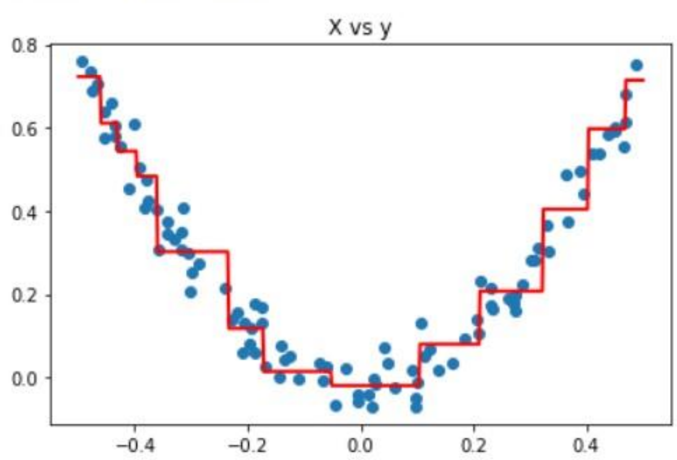
sum(regressor.predict(X_test.reshape(-1, 1)) for regressor in [tree1,tree2])

plt.figure(figsize=(14,4)) plt.subplot(121)

plt.plot(X_test, y_pred, linewidth=2,color='red')

plt.scatter(df['X'],df['y']) plt.title('X vs y')

[30]: Text(0.5, 1.0, 'X vs y')

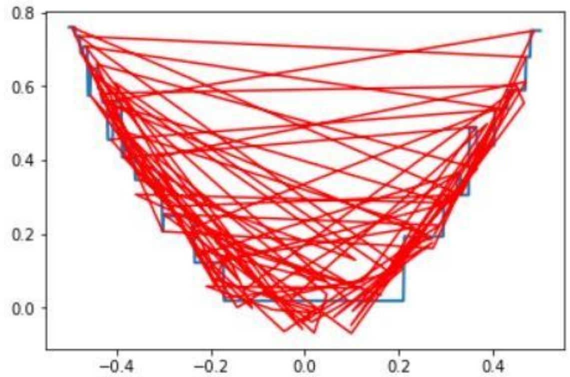


def gradient_boost(X,y,number,lr,count=1,regs=[],foo=None):

if number == 0: return else:

```
# do gradient boosting
if count > 1:
        y = y - regs[-1].predict(X)
else:
        foo = y
    tree_reg = DecisionTreeRegressor(max_depth=5, random_state=42)
tree_reg.fit(X, y)

    regs.append(tree_reg)

    x1 = np.linspace(-0.5, 0.5, 500)      y_pred = sum(lr *
regressor.predict(x1.reshape(-1, 1)) for regressor in regs)

    print(number)      plt.figure()
plt.plot(x1, y_pred, linewidth=2)
plt.plot(X[:, 0], foo,"r")
plt.show()

    gradient_boost(X,y,number-1,lr,count+1,regs,foo=foo)

np.random.seed(42) X = np.random.rand(100, 1)
- 0.5 y = 3*X[:, 0]**2 + 0.05 *
np.random.randn(100)
gradient_boost(X,y,5,lr=1)
```

5


0.8
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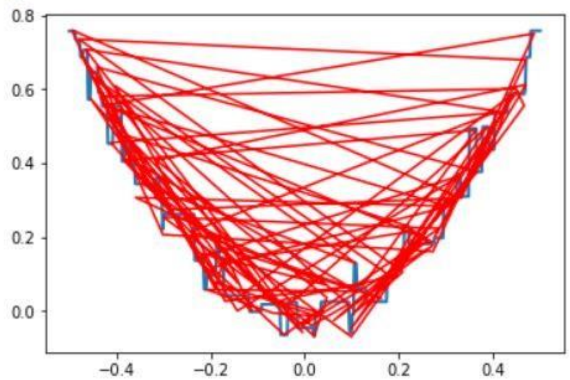
4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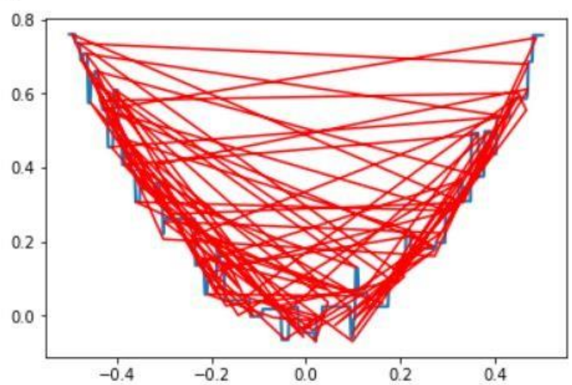
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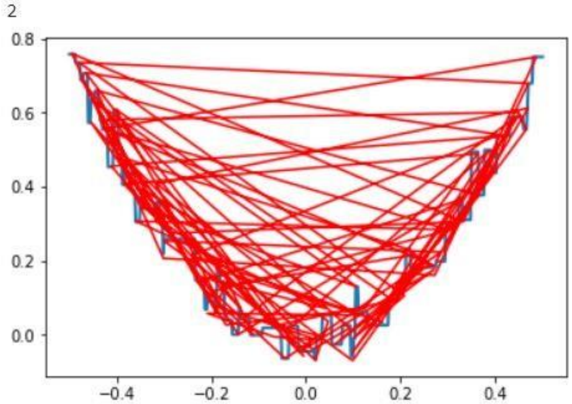
2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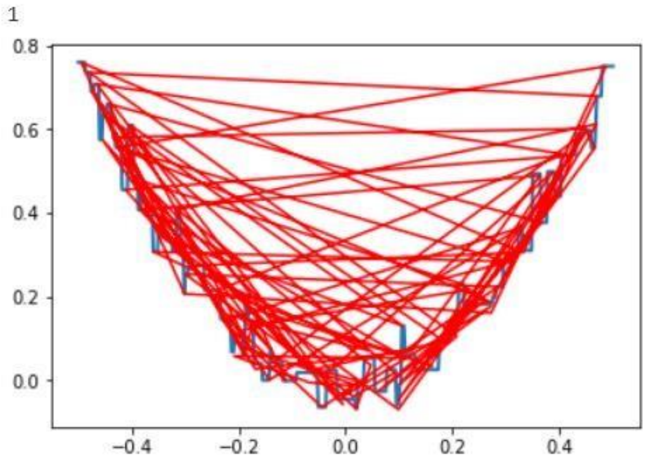

RESULT:-

Thus, the python program to implement gradient boosting for the standard uniform distribution has been successfully implemented and the results have been verified and analyzed.