EXPERIMENT:8(b)

A python program using the gradient boosting model

AIM:

To implement a python program using the gradient boosting model.

Algorithm:

Step 1: Import Necessary Libraries
Import numpy as np.
Import pandas as pd.
Import train_test_split from sklearn.model_selection.
Import DecisionTreeRegressor from sklearn.tree.
Import mean_squared_error from sklearn.metrics.

Step 2: Prepare the Data
Load your dataset into a DataFrame using pd.read_csv('your_dataset.csv').
Split the dataset into features (X) and target (y).
Use train_test_split to split the data into training and testing sets.

Step 3: Initialize Parameters
Set the number of boosting rounds (e.g., n_estimators = 100).
Set the learning rate (e.g., learning_rate = 0.1).

Initialize an empty list to store the weak learners (decision trees).
Initialize an empty list to store the learning rates for each round.

Step 4: Initialize the Base Model
Compute the initial prediction as the mean of the target values (e.g., F0 = np.mean(y_train)).
Initialize the predictions to the base model's prediction (e.g., F = np.full(y_train.shape, F0)).

Step 5: Iterate Over Boosting Rounds
For each boosting round:
Compute the pseudo-residuals (negative gradient of the loss function) (e.g., residuals
= y_train - F).
Fit a decision tree to the pseudo-residuals.
Make predictions using the fitted tree (e.g., tree_predictions = tree.predict(X_train)).
Update the predictions by adding the learning rate multiplied by the tree predictions
(e.g., F += learning_rate * tree_predictions).
Append the fitted tree and the learning rate to their respective lists.

Step 6: Make Predictions on Test Data
Initialize the test predictions with the base model's prediction (e.g., F_test =
np.full(y_test.shape, F0)).
For each fitted tree and its learning rate:

Make predictions on the test data using the fitted tree.
Update the test predictions by adding the learning rate multiplied by the tree predictions.

Step 7: Evaluate the Model
Compute the mean squared error on the training data.
Compute the mean squared error on the test data.

CODE 1:

```
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.head()
```

OUTPUT 1:

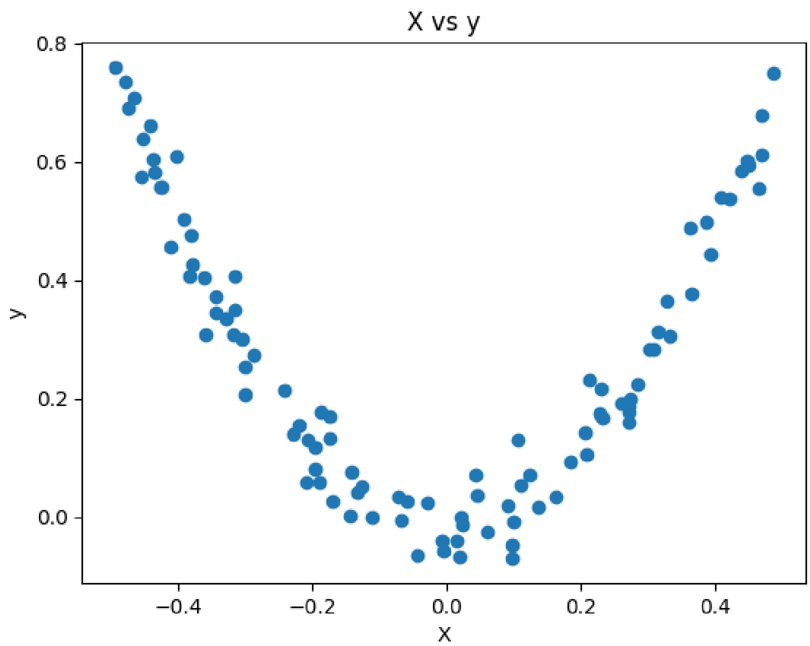
	X	y
0	-0.125460	0.051573
1	0.450714	0.594480

	X	y
2	0.231994	0.166052
3	0.098658	-0.070178
4	-0.343981	0.343986

CODE 2:

```
plt.scatter(df['X'], df['y'])
plt.title('X vs y')
plt.xlabel('X')
plt.ylabel('y')
plt.show()
```

OUTPUT 2:



CODE 3:

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

OUTPUT 3:

	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

CODE 4:

```
df['res1'] = df['y'] - df['pred1']
df.head()
```

OUTPUT 4:

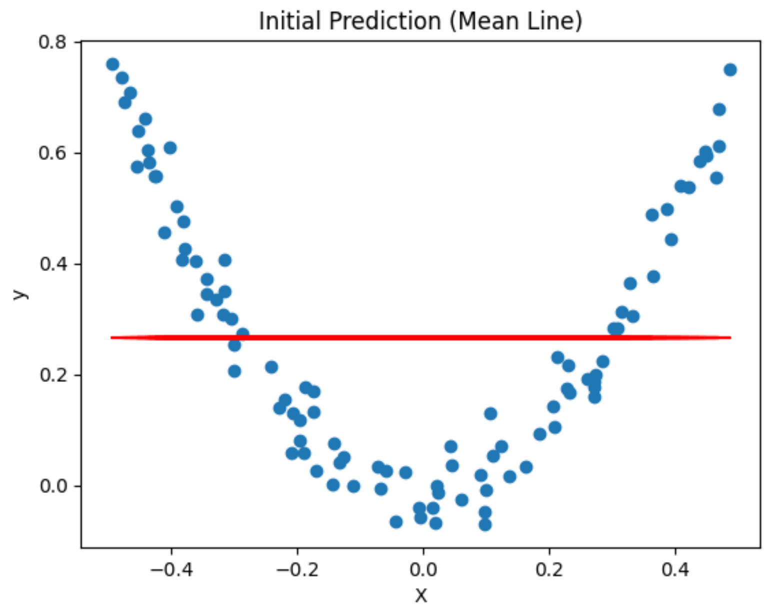
	X	y	pred1	res1
0	-0.125460	0.051573	0.265458	-0.213885
1	0.450714	0.594480	0.265458	0.329021
2	0.231994	0.166052	0.265458	-0.099407
3	0.098658	-0.070178	0.265458	-0.335636

	X	y	pred1	res1
4	-0.343981	0.343986	0.265458	0.078528

CODE 5:

```
plt.scatter(df['X'], df['y'])
plt.plot(df['X'], df['pred1'], color='red')
plt.title('Initial Prediction (Mean Line)')
plt.xlabel('X')
plt.ylabel('y')
plt.show()
```

OUTPUT 5:

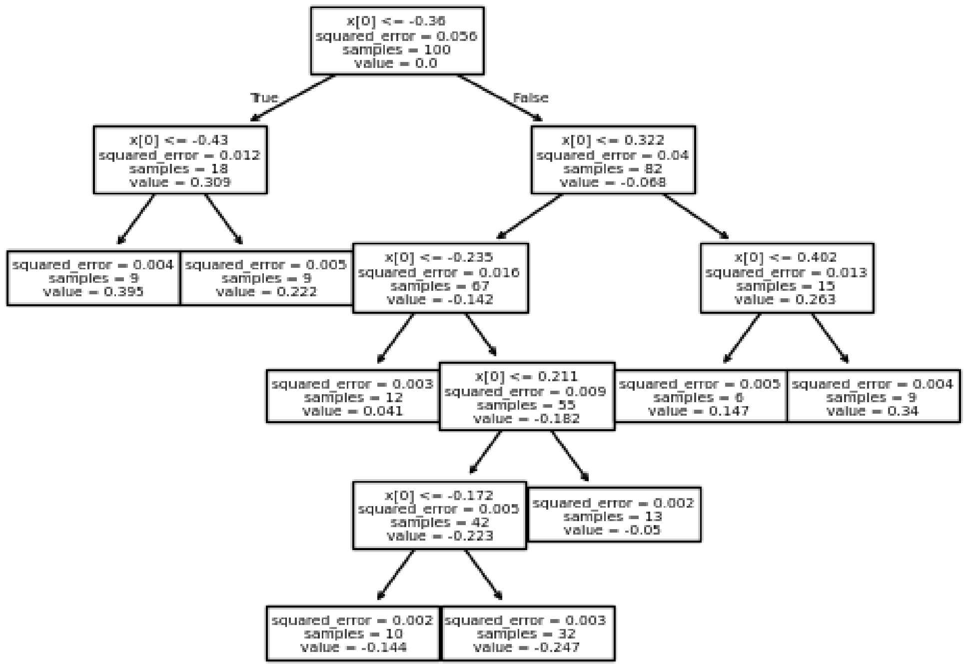


CODE 6:

```
from sklearn.tree import DecisionTreeRegressor, plot_tree
tree1 = DecisionTreeRegressor(max_leaf_nodes=8)
```

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


plot_tree(tree1)

plt.show()
```

OUTPUT 6:

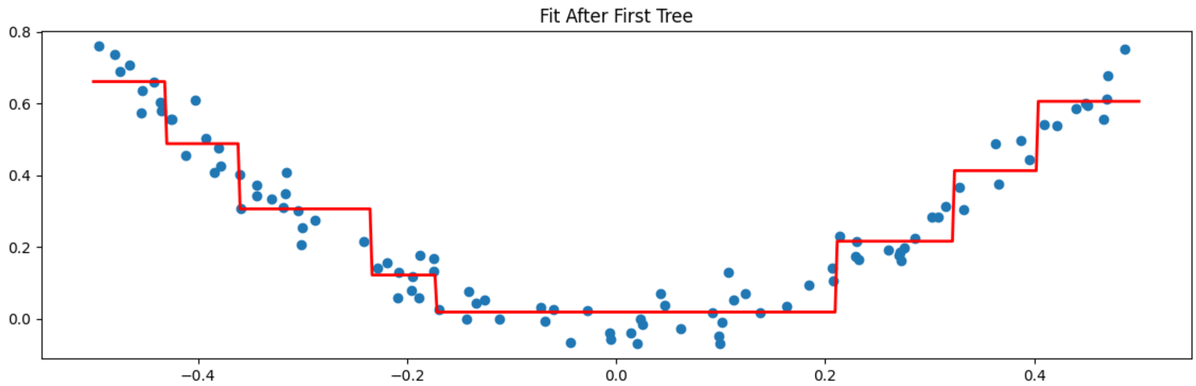


CODE 7:

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

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

plt.title("Fit After First Tree")
```

plt.show()

OUTPUT 7:

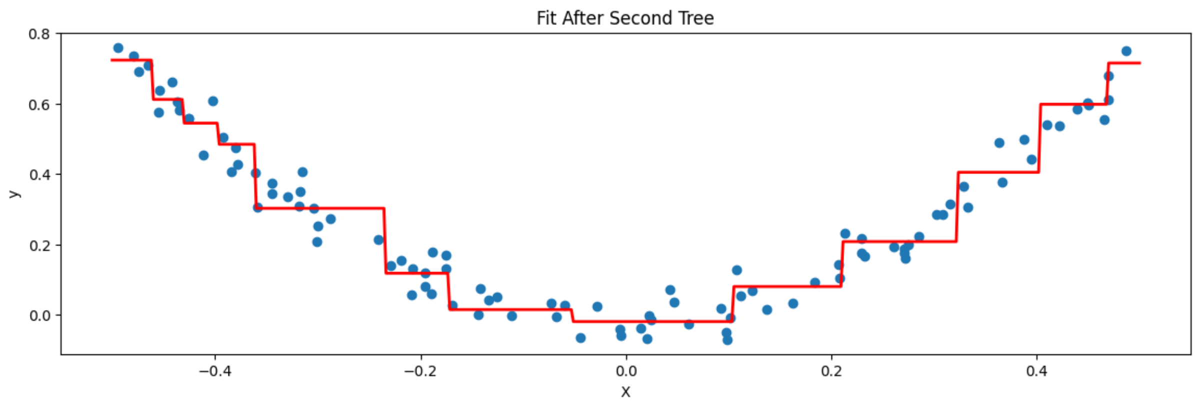


CODE 8:

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

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


tree2 = DecisionTreeRegressor(max_leaf_nodes=8)

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


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

y_pred = df['pred1'].iloc[0] + tree1.predict(X_test.reshape(-
1,1)) + tree2.predict(X_test.reshape(-1,1))


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

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

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

plt.title('Fit After Second Tree')
```

```
plt.xlabel("X")

plt.ylabel("y")

plt.show()
```

OUTPUT 8:



CODE 9:

```
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)
```

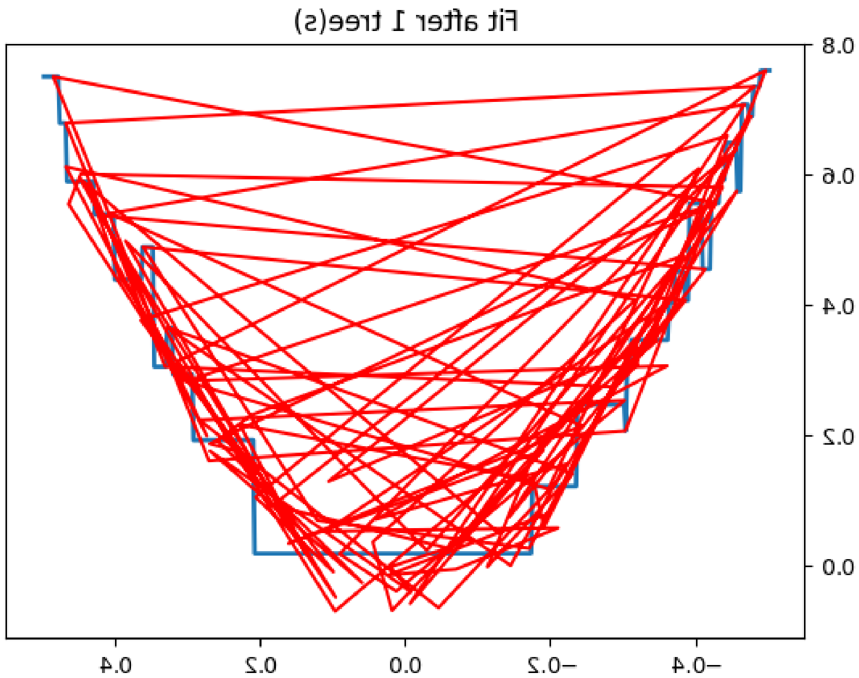
```
    regs.append(tree_reg)

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

    plt.figure()
    plt.plot(x1, y_pred, linewidth=2)
    plt.plot(X[:, 0], foo, "r")
    plt.title(f"Fit after {count} tree(s)")
    plt.show()

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

CODE 10:

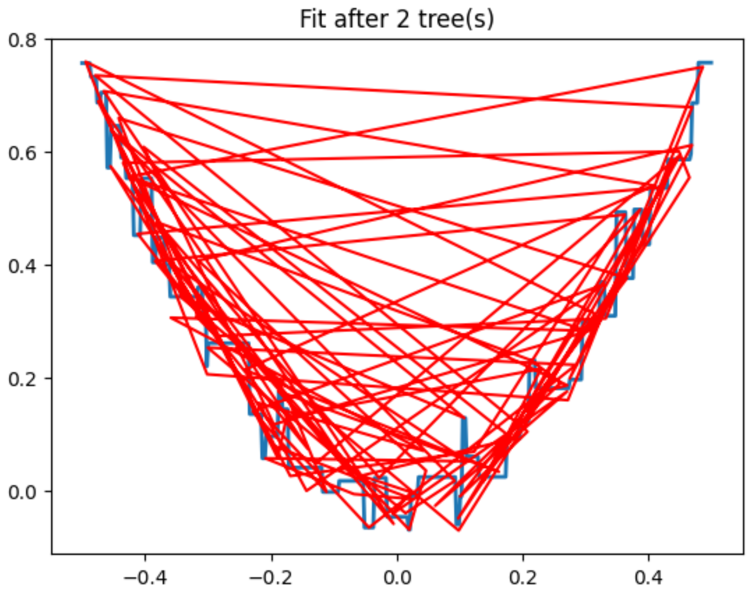
```
np.random.seed(42)
X = np.random.rand(100, 1) - 0.5
y = 3*X[:, 0]**2 + 0.05 * np.random.randn(100)

gradient_boost(X, y, 5, lr=1)
```

OUTPUT 10:

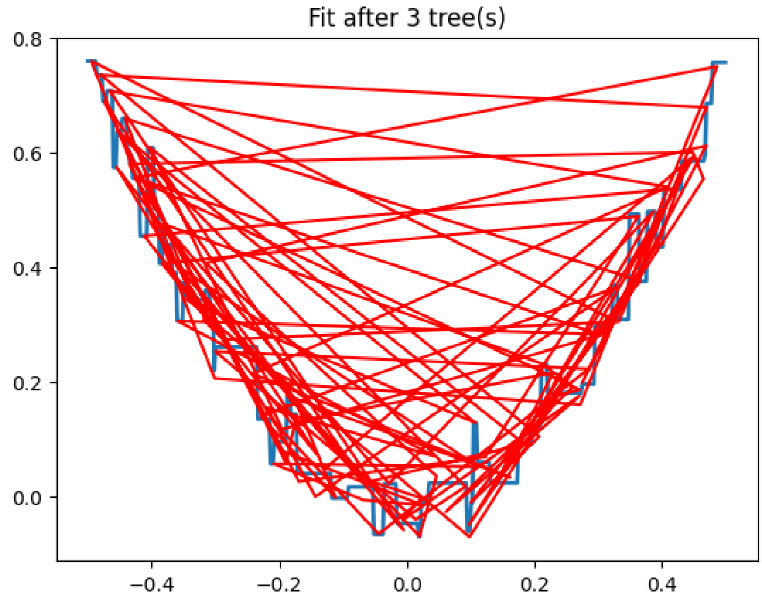
Iteration: 1



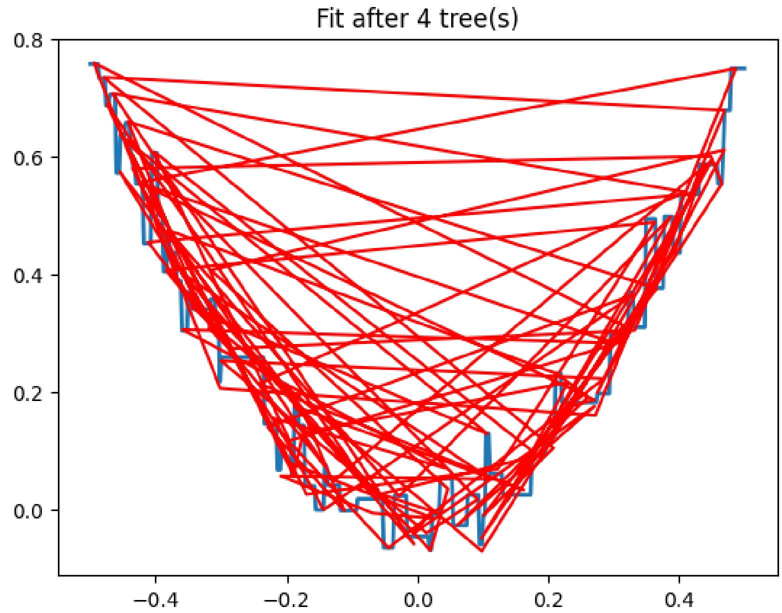
Iteration: 2



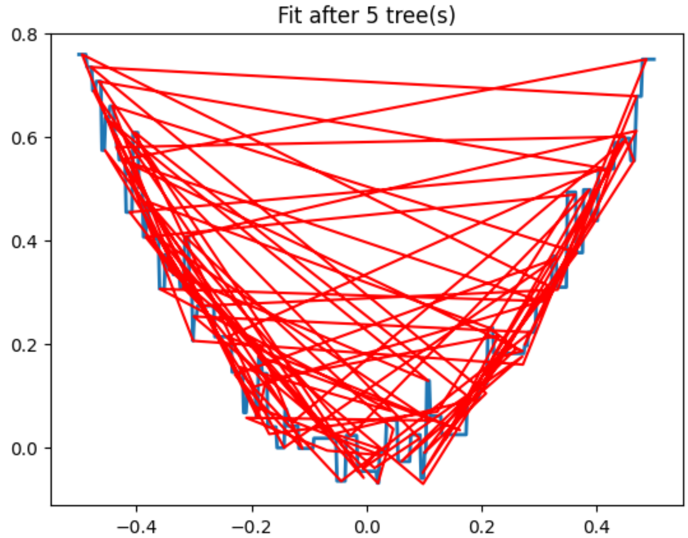
Iteration: 3



Iteration: 4



Iteration: 5



RESULT:

Thus a python program to implement gradient boosting is written and the output is verified.