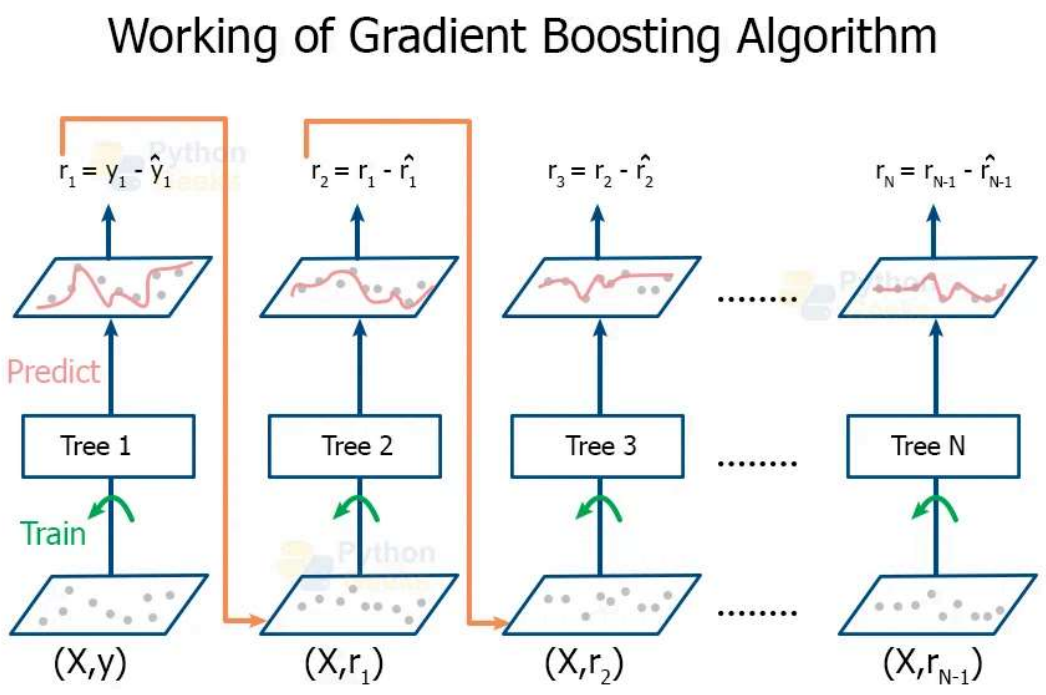
Gradient Boosting Algorithm

It is an ensemble technique that combines the predictions of multiple weak learners, *typically decision trees*, sequentially.



It is a powerful algorithm to find any nonlinear relationship between input and target.

Advantages of Gradient Boosting

- Robustness to Missing Values and Outliers
- Effective Handling of High Cardinality Categorical Features

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Gradient Boosting is a machine learning technique used for classification and regression tasks.

This article aims to provide you with all the details about Gradient Boosting Regressor algorithm, including Python code from scratch.

Implementing Gradient Boost Regressor in Python

In [ ]:
```
import numpy as np
import matplotlib.pyplot as plt
```

Let's build a polynomial data that will represent this equation: **y = 0.5x^2 + 0**.9x + 2

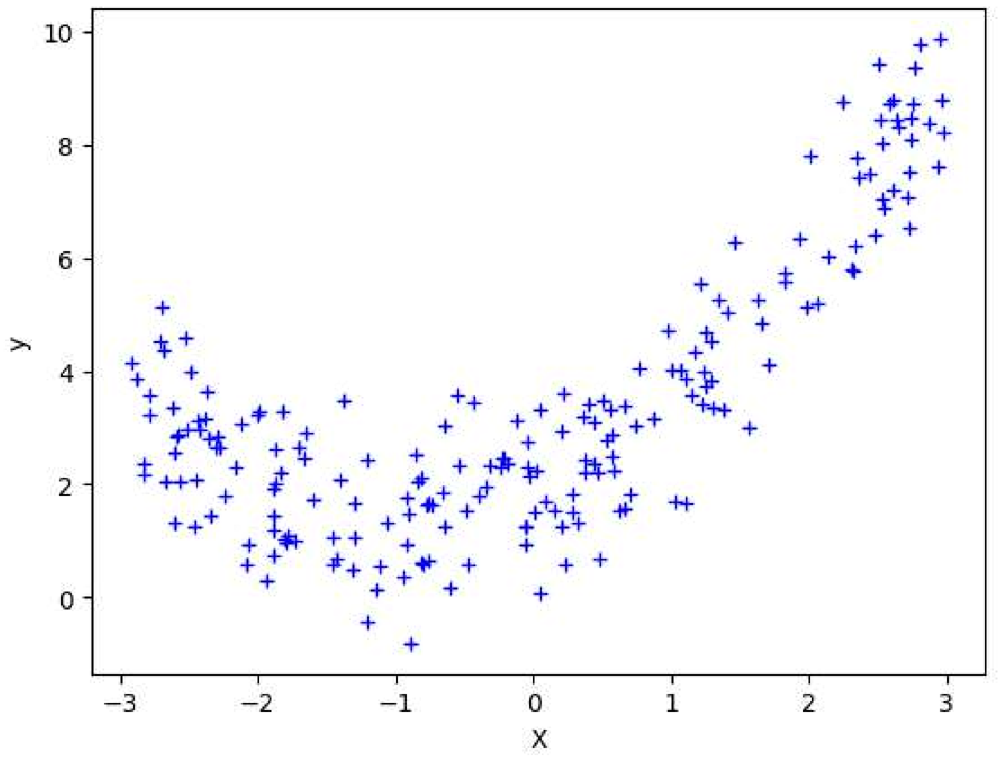
Generating synthetic data with a Quadratic relationship using NumPy and randomness

In [ ]:
```
# X values randomly generated in the range [-3, 3]
X = 6 * np.random.rand(200, 1) - 3

# Creating a quadratic relationship in the data with some noise
y = 0.5 * X**2 + 0.9 * X + 2 + np.random.randn(200, 1)
```

Let's plot our generated data.

In [ ]:
```
plt.plot(X, y,'b+')
plt.xlabel("X")
plt.ylabel("y")
plt.show()
```



In [ ]:
```
import pandas as pd
```

In [ ]:
```
# Combine X and y arrays into a single DataFrame
df = pd.DataFrame({'X': X.flatten(), 'y': y.flatten()})

# Display the first few rows of the DataFrame
print(df.head())
```

```
          X         y
0 -1.592798  1.708897
1  2.728114  7.508357
2  1.459935  6.287942
3 -2.709505  4.521559
4  1.307548  3.333105
```

Train test split

In [ ]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score
```

In [ ]:
```
train_input, test_input, train_target, test_target = train_test_split(df['X'].values.reshape
```

In [ ]:
```
print(train_input.shape)
print(train_target.shape)
```

```
(160, 1)
(160,)
```

In [ ]:
```
train_input
```

In [ ]:
```
from sklearn.tree import DecisionTreeRegressor
```

Building our own Gradient Boosting Regressor

1. **Initialization**:

- Initialize the Gradient Boosting Regressor with parameters such as the number of estimators (trees), learning rate, and maximum depth of each decision tree.
- Initialize an empty list to store the decision trees (dts) that will form the ensemble.

2. **Training (fitting)**:

- Initially, set the first prediction (F0) as the mean of the target column.
- For each estimator (decision tree):
  - Calculate the residual, which represents the difference between the actual target values and the current ensemble prediction.
  - Train a decision tree regressor to predict these residuals, with a maximum depth specified.
  - Get the predictions (gamma) of this new decision tree on the training inputs.
  - Update the ensemble predictions by adding the predictions of this tree, scaled by the learning rate.
  - Store the trained decision tree in the list of decision trees.

3. **Prediction**:

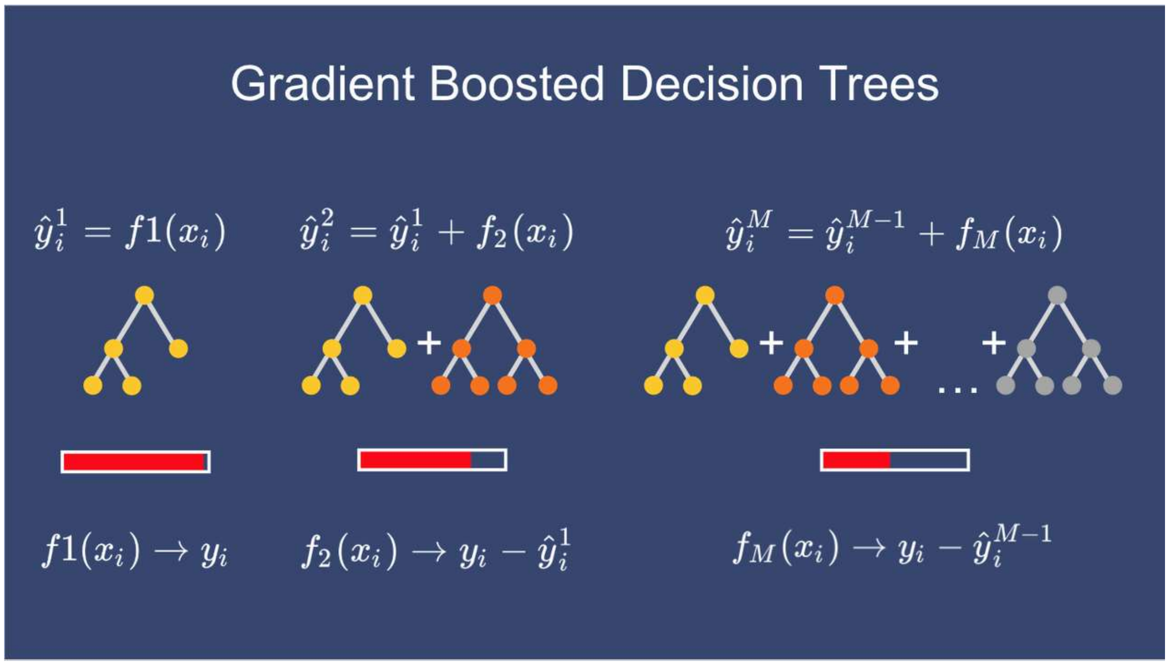
- To make predictions:
  - Initialize the predictions with the initial prediction value (F0), which is the mean of the target column.
  - For each decision tree in the ensemble:
    - Get the predictions of the decision tree on the test inputs.
    - Scale these predictions by the learning rate.
    - Add these scaled predictions to the current ensemble predictions.
- Return the final predictions.

4. **Interpretation**:

- The algorithm iteratively improves predictions by fitting new decision trees to the residuals of the previous predictions.
- Each decision tree focuses on capturing the errors (residuals) of the ensemble, gradually reducing the overall prediction error.

5. **Ensemble Building**:

- The final prediction is a combination of the predictions made by all the decision trees in the ensemble, each weighted by the learning rate.
- By adding new weak learners (decision trees) to the ensemble and updating the predictions iteratively, the algorithm builds a strong predictive model that can capture complex relationships in the data.


Gradient Boosted Decision Trees
$\hat{y}_i^1 = f1(x_i)$
$\hat{y}_i^2 = \hat{y}_i^1 + f_2(x_i)$
$\hat{y}_i^M = \hat{y}_i^{M-1} + f_M(x_i)$
$f1(x_i) \rightarrow y_i$
$f_2(x_i) \rightarrow y_i - \hat{y}_i^1$
$f_M(x_i) \rightarrow y_i - \hat{y}_i^{M-1}$

In [ ]:
```
class GradientBoostingRegressor():

    def __init__(self, n_estimators = 50, learning_rate = 0.1, max_depth = 1):
        self.n_estimators = n_estimators
        self.learning_rate = learning_rate
        self. max_depth = max_depth
        self.dts = [] # Decision Trees


    def fit(self, train_inputs, train_target):

        # Since we are using Least Square as Loss Function
        # The First Prediction will be the Mean(Target Column)
        self.F0 = train_target.mean()

        # First Model
        Fm = self.F0

        # For each estimator
        for _ in range(self.n_estimators):

            # Calculating residual (pseudo-residuals in case of GB)
            residual = train_target - Fm

            # Fitting Regression Tree
            dt = DecisionTreeRegressor(max_depth = self.max_depth, random_state = 0)
            # we get the same train and test sets across different executions.

            dt.fit(train_inputs, residual)

            # Calculating Gamma - the predictions of the new model
            gamma = dt.predict(train_inputs)

            # Updating Ensemble Predictions
            Fm += self.learning_rate * gamma

            # Storing the trained decision tree
            self.dts.append(dt)


    def predict(self, test_inputs):
        # Initialize predictions with F0 (the mean of the target column)
        predictions = np.full(len(test_inputs), self.F0)

        # Add predictions of each weak learner multiplied by its learning rate
        for dt in self.dts:
            predictions += self.learning_rate * dt.predict(test_inputs)

        return predictions
```

In [ ]:

```
bgr = GradientBoostingRegressor(max_depth = 1, n_estimators = 500, learning_rate = 0.1)
bgr.fit(train_input, train_target)
```

In [ ]:

```
y_pred = bgr.predict(test_input)
```

In [ ]:

```
r2_score(test_target,y_pred)
```

Out[ ]:

```
0.7656349948868615
```

Validating the Accuracy

In [ ]:

```
from sklearn.ensemble import GradientBoostingRegressor
```

In [ ]:

```
sklearn_gbm = GradientBoostingRegressor(
    n_estimators=500,
    learning_rate=0.1,
    max_depth=1
)
sklearn_gbm.fit(train_input, train_target)
y_gbm_pred = sklearn_gbm.predict(test_input)
r2_score(test_target,y_gbm_pred)
```

Out[ ]:

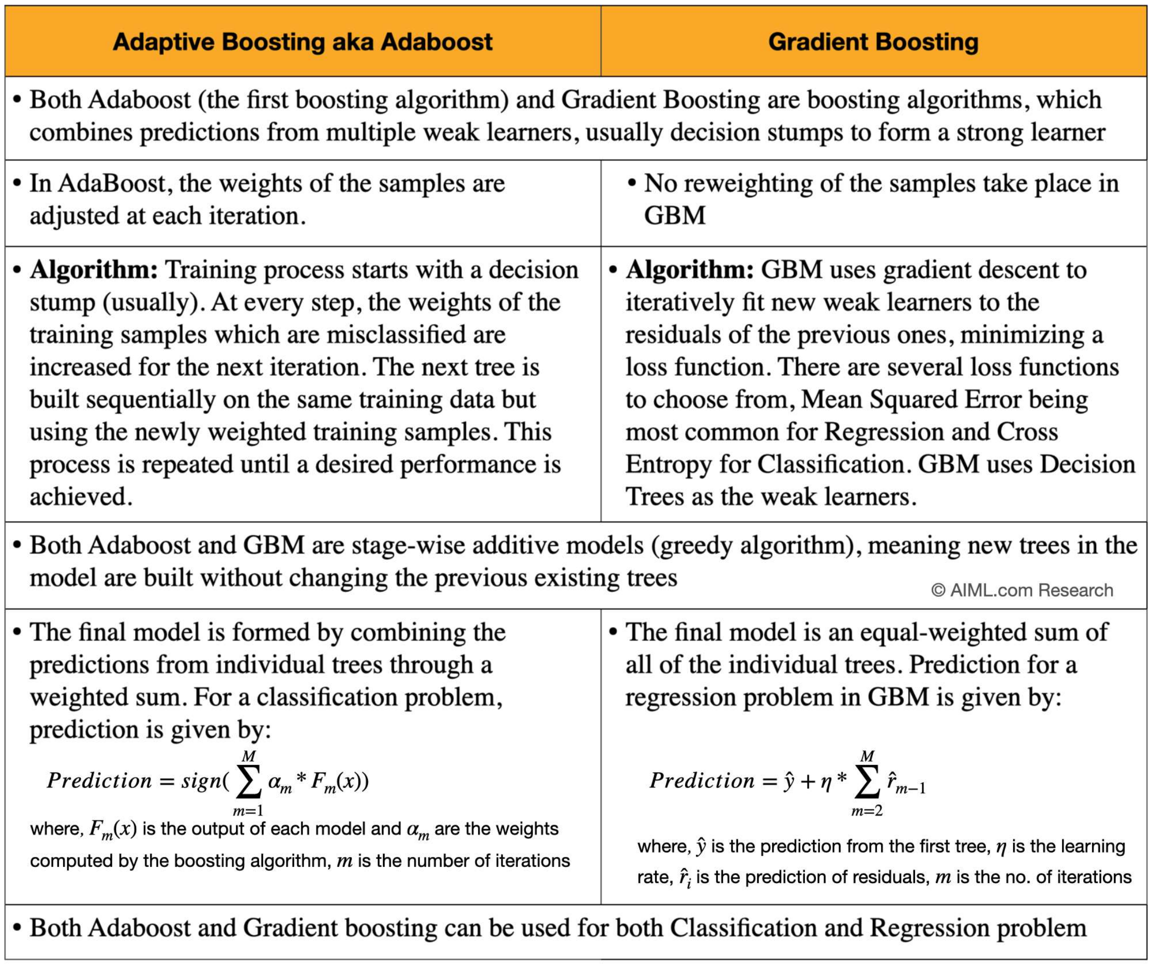
```
0.7656349948868615
```

As you can see in the output above, both models have exactly the same

Conclusion

The class that we build, uses the **Least Square Loss Function** (one of the options of gradient boosting algorithm) to solve Regression Problems.

Difference between Adaboost and Gradient Boosting algorithms



Adaptive Boosting aka Adaboost	Gradient Boosting
• Both Adaboost (the first boosting algorithm) and Gradient Boosting are boosting algorithms, which combines predictions from multiple weak learners, usually decision stumps to form a strong learner	
• In AdaBoost, the weights of the samples are adjusted at each iteration.	• No reweighting of the samples take place in GBM
• **Algorithm:** Training process starts with a decision stump (usually). At every step, the weights of the training samples which are misclassified are increased for the next iteration. The next tree is built sequentially on the same training data but using the newly weighted training samples. This process is repeated until a desired performance is achieved.	• **Algorithm:** GBM uses gradient descent to iteratively fit new weak learners to the residuals of the previous ones, minimizing a loss function. There are several loss functions to choose from, Mean Squared Error being most common for Regression and Cross Entropy for Classification. GBM uses Decision Trees as the weak learners.
• Both Adaboost and GBM are stage-wise additive models (greedy algorithm), meaning new trees in the model are built without changing the previous existing trees © AIML.com Research	
• The final model is formed by combining the predictions from individual trees through a weighted sum. For a classification problem, prediction is given by: $Prediction = sign(\sum_{m=1}^{M} \alpha_m * F_m(x))$ where, $F_m(x)$ is the output of each model and α_m are the weights computed by the boosting algorithm, m is the number of iterations	• The final model is an equal-weighted sum of all of the individual trees. Prediction for a regression problem in GBM is given by: $Prediction = \hat{y} + \eta * \sum_{m=2}^{M} \hat{r}_{m-1}$ where, $\hat{y}$ is the prediction from the first tree, η is the learning rate, $\hat{r}_i$ is the prediction of residuals, m is the no. of iterations
• Both Adaboost and Gradient boosting can be used for both Classification and Regression problem	

> Stay tuned for Gradient Boosting Classifer Models and Don't forget to **Star** this Github Repository for more such contents and consider **sharing with others**.

```
In [ ]:
```