

# Gradient Boosting Algorithms

Epoch IIT Hyderabad

Himani Agrawal  
MA22BTECH11008

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## Introduction

Gradient Boosting is a popular machine learning algorithm that belongs to the supervised learning technique. It is a boosting method that combines several weak learners into strong learners. Each new model is trained to minimize the loss function of the previous model using gradient descent.

## Working of Algorithm

1. **Initialization:** The algorithm starts by predicting a constant value for all instances in the dataset. This initial prediction can be the mean (for regression problems) or the most frequent class (for classification problems).
2. **Gradient Calculation:** The residuals (differences between the predicted and actual values) are calculated. These residuals are the negative gradient of the loss function.
3. **Weak Learner Construction:** A decision tree is fitted to the residuals from the previous step. This tree is a 'weak learner' and is designed to predict a small step towards the residuals.
4. **Prediction Update:** The predictions are updated by adding the predictions from the new weak learner, scaled by a learning rate.
5. **Iterative Learning:** Steps 2-4 are repeated until a specified number of weak learners have been created, or if the residuals

can no longer be reduced. Each iteration involves the following formula

$$F_{i+1} = F_i - f_i$$

Where:

- $F_i$  is the strong model at step  $i$ .
- $f_i$  is the weak model at step  $i$ .

In each iteration, the algorithm computes the gradient of the loss function with respect to the predictions of the current ensemble and then trains a new weak model to minimize this gradient. The predictions of the new model are then added to the ensemble, and the process is repeated until a stopping criterion is met.

### Formulas used

The Gradient Boosting algorithm uses the following formulas:

- Residual Calculation:  $r_i = y_i - F(x_i)$

Where  $r_i$  is the residual for the  $i$ th instance,  $y_i$  is the actual value, and  $F(x_i)$  is the predicted value.

- Weak Learner Prediction:  $h_i(x) = r_i$

Where  $h_i(x)$  is the prediction of the  $i$ th weak learner.

- Prediction Update:  $F_{i+1}(x) = F_i(x) + \eta * h_i(x)$

Where  $F_{i+1}(x)$  is the updated prediction,  $F_i(x)$  is the current prediction,  $\eta$  is the learning rate, and  $h_i(x)$  is the prediction of the  $i$ th weak learner