

Intuition of Gradient Boosting

Regression vs. Classification

Regression

Loss: $L = \frac{1}{2}(y - \hat{y})^2$

Gradient (negative): $-\frac{dL}{d\hat{y}} = y - \hat{y}$

→ Each tree fits the **residual (numeric error)**.

Intuition:

The model corrects the *difference* between predicted and true values.

Classification

Loss: $L = -[y \log(p) + (1 - y) \log(1 - p)]$

Gradient (negative): $-\frac{dL}{dF(x)} = y - p$

→ Each tree fits the **probability residual** (difference between true label and predicted probability).

Intuition:

The model corrects how much the predicted probability *over- or underestimates* the truth.

Key Takeaway

Both regression and classification use the same idea:

■ Each new tree learns to fix what the previous trees got wrong.

The only difference is the space of residuals — numeric values vs. probabilities.