

Gradient Boosting Algorithm [Boosting Algorithm]

Regression											
x_1		x_2									
Exp	Degree										
→ 2	B.E	50k	75	-25	-23	72.7	-22.2	-			
→ 3	M.Com	70k	75	-5	-3	74.7	-4.7	-			
5	Master	80k	75	5	3	75.3	4.7	-			
6	PhD	100k	75	25	20	77	23	-			
		75k									

Step 1: Create a Base Model

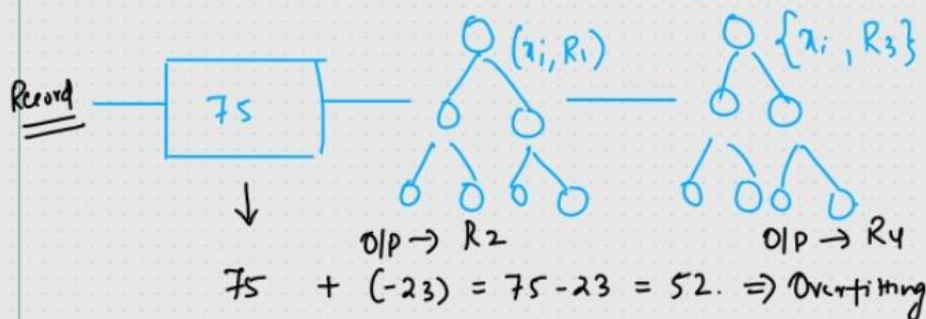
Let's Assume

75k

$$\text{Average} = \frac{50 + 70 + 80 + 100}{4} = 75k$$

Step 2: Compute Residuals or Error

Step 3: We construct next sequential Decision Tree with
i/p x_i and o/p Residuals $[R_i]$.



$$\text{Predicted} = 75 + \alpha(-23)$$

$$= 75 + 0.1(-23)$$

$$= 72.7$$

$$\alpha = \text{Learning Rate} \quad \underline{0.1}$$

$$\alpha = 0.1$$

Final function

Base learner

M_1

$$F(x) = d_0 h_0(x) + d_1 (h_1(x)) + d_2 (h_2(x)) + d_3 (h_3(x)) + \dots + d_n (h_n(x))$$

$$F(x) = \sum_{i=0}^n d_i h_i(x)$$

\Rightarrow Gradient Boost

① Xgboost classifier

= Extreme Gradient Boost

$$0 + 0.1(0.33) = 0.033$$

Dataset

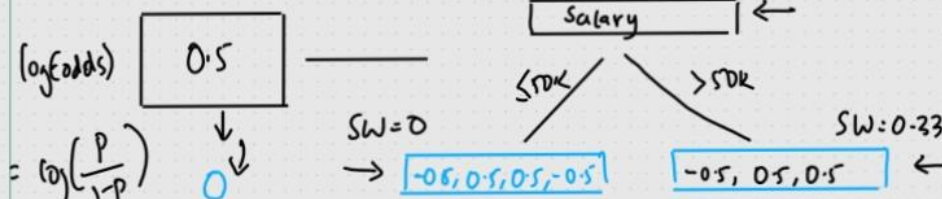
0.52

<u>Salary</u>	<u>Credit</u>	<u>y</u> Approval	<u>R1</u>	\hat{y}	<u>R2</u>
<=50K	B	0	-0.5	0.52	-0.02
<=50K	G	1	0.5	0.58	0.42
<=50K	G	1	0.5	-	-
>50K	B	0	-0.5	-	-
>50K	G	1	0.5	-	-
>50K	N	1	0.5	-	-
<=50K	N	0	-0.5	-	-

① Step 1 : Base Model

SW: 0.142

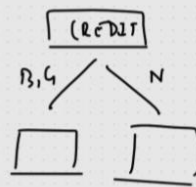
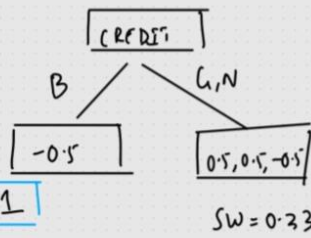
$[-0.5, 0.5, 0.5, -0.5, -0.5, 0.5, 0.5]$



Step 3: We calculate

Similarity weight

$$= \frac{(\sum \text{Residual})^2}{\sum Pr(1-Pr)}$$



71

↓
0 to 1

$\sigma = 0.1$

Model o/p = $\sigma \left[\frac{0 + \alpha(1)}{0.1} \right] = \frac{1}{1 + e^{-0.1}} = 0.52$

$\sigma = \frac{1}{1 + e^{-z}}$

S.W (CRFDT) = $\frac{(-0.5 + 0.5 + 0.5 - 0.5)^2}{4} \Rightarrow 0$

S.W (CRFDT) = $\frac{0.25}{0.75} = 0.33$

$1 \Leftarrow 0.5(1-0.5) + 0.5(1-0.5) + 0.5(1-0.5) + 0.5(1-0.5)$

Gain = $0 + 0.33 - 0.142 = 0.19$

Final o/p

Binary classification

→ Logistic Regression ⇒ log loss

Test Data → 0.5

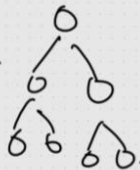
↓

$\log(\text{odds}) = \log\left(\frac{p}{1-p}\right)$

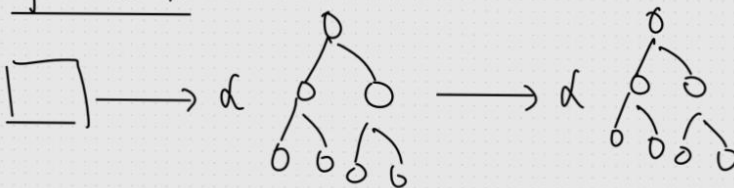
$= \log\left(\frac{0.5}{0.5}\right)$

$= \log 1$

$= 0$



Xgboost classifier



o/p = $\sigma \left[\text{Base learner} + \alpha_1(DT_1) + \alpha_2(DT_2) + \dots + \alpha_n(DT_n) \right]$

↓ log loss