

XGBoost

Xtream Gradient Boosting

It is also works for both problem, Regression and classification.

It is used to solve complex data problem.

It is implemented in C++ and provides interface for python and other language

Incorporate regularization L_1 & L_2 for overfitting

Support parallel tree construction to speed up training.

Handle missing data automatically

Pros -

- ① High performance
- ② speed and scalability
- ③ Flexibility

Cons -

- ① Complexity
- ② Computational Resource
- ③ Not ideal for unstructured data

After 1st step

↓ Sal.	↓ Credit	Y Approved	↓ pred.	$Y - \hat{Y} = R$ (Residual)	\hat{Y}_2
≤ 50	B	0	0.5	$0 - 0.5 = -0.5$	0
≤ 50	G	1	0.5	$1 - 0.5 = 0.5$	0
≤ 50	G	1	0.5	$1 - 0.5 = 0.5$	1
> 50	B	0	0.5	$0 - 0.5 = -0.5$	0
> 50	G	1	0.5	$1 - 0.5 = 0.5$	1
> 50	N	1	0.5	$1 - 0.5 = 0.5$	0
≤ 50	N	0	0.5	$0 - 0.5 = -0.5$	1

Step-1 Base model

class 0 and 1

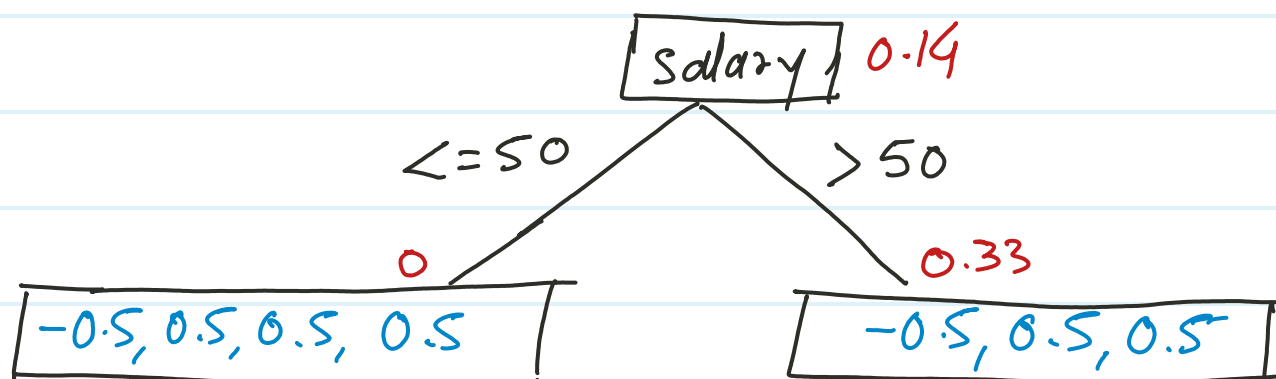
$$\frac{0+1}{2} = 0.5$$

If called probability 0.5

To calculate residual initially use probability

After getting residual construct a tree

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



Doesn't matter how category will be there, it split or construct the tree with two leaf only mean binary tree only created.

step-2

calculate the similarity weight

$$\text{Similarity wt} = \frac{\sum (\text{Residual})^2}{\sum [P_r (1 - P_r)]}$$

1st leaf

$$\begin{aligned} \leq 50 &= \frac{[-0.5 + 0.5 + 0.5 - 0.5]^2}{[0.5(1+0.5) + 0.5(1-0.5) + 0.5(1-0.5) - 0.5(1+0.5)]} \end{aligned}$$

$$<=50 = \frac{0}{1} = 0$$

2nd leaf

$$\underline{\underline{>50}} = \frac{[-0.5 + 0.5 + 0.5]^2}{[0.5(1+0.5) + 0.5(1-0.5) + 0.5(1-0.5)]}$$

$$>50 = \frac{0.25}{0.75} = \frac{1}{3} = 0.33$$

3rd root

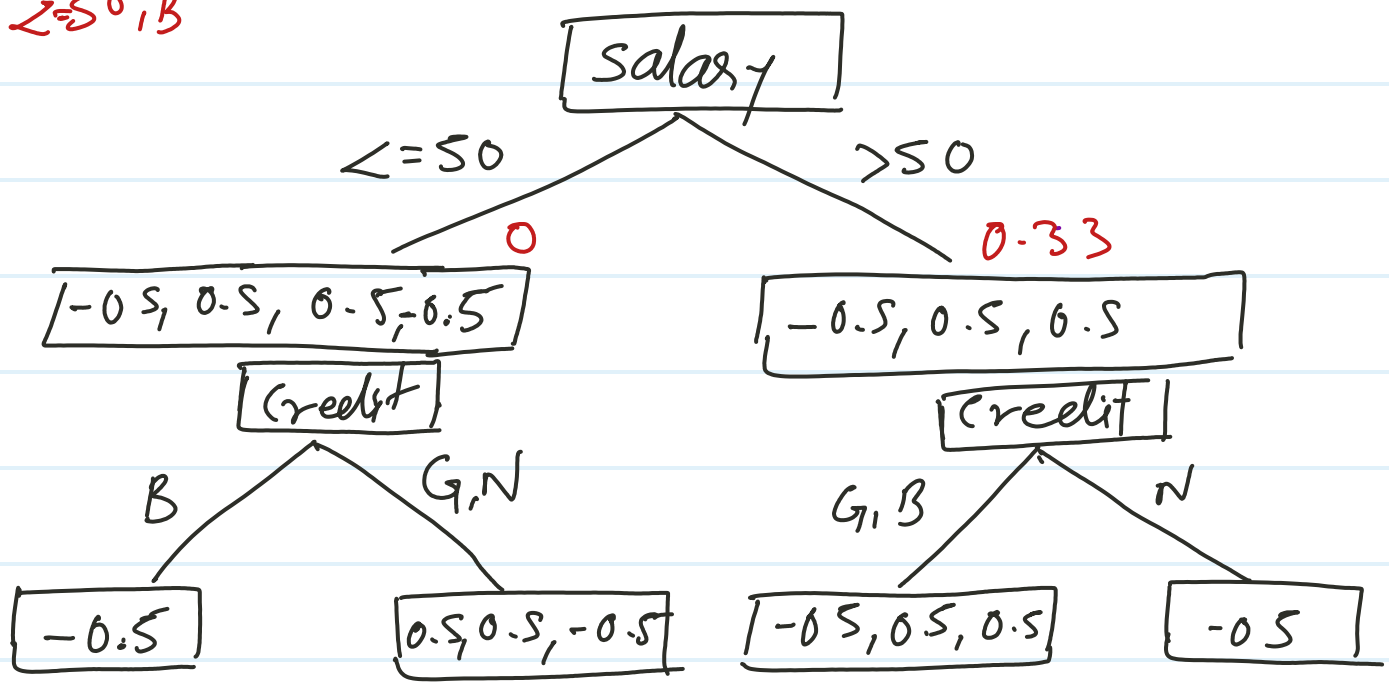
$$\text{salary} = \frac{[-0.5 + 0.5 + 0.5 - 0.5 + 0.5 + 0.5 - 0.5]^2}{[0.5(1+0.5) + 0.5(1-0.5) + 0.5(1-0.5) + 0.5(1+0.5) + 0.5(1-0.5) + 0.5(1-0.5) + 0.5(1+0.5)]}$$

$$\text{salary} = \frac{0.25}{1.75} = 0.14$$

$$\begin{aligned} \text{Gain} &= (\text{Sm wt}_1 + \text{Sm wt}_2) - \text{Sm wt Root} \\ &= (0 + 0.33) - 0.14 \\ &= 0.21 \end{aligned}$$

For each feature we calculate gain, whichever is higher will be consider as root

$z=50, B$



$$Sm\ wt_1 = \frac{(-0.5)^2}{[0.5(1+0.5)]} = \frac{0.25}{0.75} = \underline{\underline{0.33}}$$

$$Sm\ wt_2 = \frac{(0.5 + 0.5 - 0.5)^2}{[0.5(1-0.5) + 0.5(1-0.5) + 0.5(1+0.5)]}$$

$$= \frac{0.25}{0.25 + 0.25 + 0.75} = 0.2$$

$$Gain = (Sm\ wt_1 + Sm\ wt_2) - Sm\ wt\ root$$

$$= (0.33 + 0.2) - 0$$

$$= 0.53$$

$$swt_1 = \frac{(-0.5 + 0.5 + 0.5)^2}{[0.5(1+0.5) + 0.5(1-0.5) + 0.5(1-0.5)]}$$

$$= \frac{0.25}{1.25} = 0.2$$

$$swt_2 = \frac{(-0.5)^2}{[0.5(1+0.5)]}$$

$$= \frac{0.25}{0.75} = 0.33$$

$$\begin{aligned} \text{Gain} &= (0.2 + 0.33) - 0.33 \\ &= 0.2 \end{aligned}$$

After this we check "cover value" for post pruning, $[Pr(1-Pr)]$

$$\text{Cover value} = 0.5(1-0.5) = 0.25$$

If cover value greater than the gain value then we will use post pruning otherwise build continue tree

in our case gain value

$$0.53 > 0.25$$

we build continue tree.

we calculate 1st decision tree, we can build any number of decision tree once residuals are calculated.

Now for predicting new record first we use odd ratio

$$\text{odd ratio} = \log\left(\frac{P}{1-P}\right)$$

Suppose we are predicting, < 50 , B

First calculate base model

$$= \frac{0.5}{1-0.5}$$

$$= \frac{\cancel{0.5}}{\cancel{0.5}} = 1 = \ln(1) = 0$$

Then we use function of xGBoost

$$\Rightarrow \sigma(BM + \alpha \text{ smwt})$$

σ = sigmoid activation function

α = learning rate (0-1)

$$\Rightarrow \sigma(0 + 0.1 (\text{smwt of leaf}))$$

$$\Rightarrow \sigma[0 + 0.1 (0.33)]$$

$$\Rightarrow \sigma(0.033)$$

$$\frac{1}{1 + e^{(0.033)}}$$

$$\Rightarrow \sigma = \frac{1}{1 + e^{(0.033)}}$$

$$\Rightarrow \boxed{\sigma = 0.492}$$

This is our new probability for new record

Salary	credit	App	R_1	New prob	R_2
≤ 50	B	0	-0.5	0.4	$0 - 0.4 = -0.6$
≤ 50	G	1	0.5	0.5	$1 - 0.5 = 0.5$
> 50	B	1	0.5	0.6	$1 - 0.6 = 0.4$
≤ 50	N	1	0.5	0.3	$1 - 0.3 = 0.7$
> 50	G	0	-0.5	0.2	$0 - 0.2 = -0.2$

Again based on new Residual R_2 we will build new decision tree

Final model formula will be

$$= \alpha [BM + \alpha \cdot DT_1 + \alpha \cdot DT_2 + \dots + \alpha \cdot DT_n]$$

XGBoost classification