

Random Forests

A Random forest is a machine learning algorithm that builds many decision trees and then combines their results to make a final decision.

Advantages :-

- ① High Accuracy : usually better than single trees
- ② Handles missing data well
- ③ Reduces overfitting
- ④ Works well for both regression & classification

Disadvantages :-

- ① Slower \rightarrow many trees \rightarrow more computation
- ② Less interpretable \rightarrow hard to visualise whole forest
- ③ Takes more memory

Usage :-

- ① Finance fraud detection, loan approval
- ② Healthcare disease prediction from symptom
- ③ E-commerce sentiment review
- ④ Agriculture crop yield prediction
- ⑤ Education student performance prediction.

Main Goal :- Reduce overfitting & improving accuracy

Algorithm with example :-

ID	Age	Income	BuyS - Computer
1	≤ 30	H	N
2	≤ 30	H	N
3	31-40	H	Y
4	> 40	M	Y
5	> 40	L	Y
6	> 40	L	N
7	31-40	L	Y
8	≤ 30	M	N
9	≤ 30	L	Y
10	> 40	M	Y

Features :- Age, Income

Target :- Buys - Computer

Step 1

Create Bootstrap Samples

(Random)

Sample 1 \Rightarrow 1, 2, 3, 4, 5, 6, 7, 8, 9, 10 (full dataset)

Sample 2 \Rightarrow 2, 4, 5, 7, 8, 9, 9, 1, 6, 3

Sample 3 \Rightarrow 3, 3, 5, 6, 7, 8, 9, 10, 10, 4

Step 2

Build Tree 1 (using Sample 1), Calculate root Gini for full data

Total Yes \Rightarrow 10s: 3, 4, 5, 7, 9, 10 \Rightarrow 6

Total No \Rightarrow 10s: 1, 2, 6, 8 \Rightarrow 4

$$G_{\text{ini}} = 1 - \left(\left(\frac{6}{10}\right)^2 + \left(\frac{4}{10}\right)^2 \right) \approx 0.48 \quad \left\{ G_{\text{ini}} = 1 - \left(P_{\text{Yes}}^2 + P_{\text{No}}^2 \right) \right.$$

Step da :- Try splitting on Age, incomes to decide root node

Calculate root Gini for 31 (Age ≤ 30)

Age $\leq 30 \rightarrow 30$

We'll try splitting on age,

Age divisions \rightarrow 1. ≤ 30 2. $31-40$ 3. > 40 Summarise in 2 categories

1. ≤ 30
2. > 30

now, split 1. Age ≤ 30 vs Age > 30

Left (≤ 30): JDS = 1, 2, 8, 9 Y=1, N=3

Right (> 30): JDS = 3, 4, 5, 6, 7, 10 Y=5, N=1

$$\text{Gini}_{\text{left}} = 1 - \frac{1}{2} [(\text{P}_{\text{left yes}})^2 + (\text{P}_{\text{left no}})^2] = .375$$

$$\text{Gini}_{\text{right}} = .278$$

Gini Age \rightarrow $.375 \times \frac{4}{10} + .278 \times \frac{6}{10} \Rightarrow .316$
(combined)
↳ weighted Gini

now, split 2. a) Income = High vs Income \neq High

$$\text{Weighted Gini} = .419$$

b) low vs others

$$\text{Weighted Gini} = .45$$

c) med vs others

$$\text{Weighted Gini} = .475$$

Now, what we have done so far is, we calculated root Gini, i.e.

Gini for full data, i.e. .48

& then we have done several splits, based on age & income.

So, the split with the lowest Gini or the one which has the max decrease from the root Gini is chosen as the Root Node.

So, best split so far was Age ($G_{\text{ini}} = 0.316$)

Root = "Age ≤ 30 ?"

Step :-

Left Node ($\text{Age} \leq 30$): JDS $\Rightarrow 1, 2, 8, 9$

$$\gamma=1, N=3, G_{\text{ini}} = 0.375$$

Try splitting on income again for left Node

• High (with Age ≤ 30) \Rightarrow JDS 1, 2 $\rightarrow N & N \rightarrow G_{\text{ini}} = 0$

Best split \Rightarrow Income High vs others

Left leafs

High \rightarrow NO

Medium/Low \rightarrow further split possible

• Med vs Low,

Med \rightarrow (JDS) \rightarrow NO $\rightarrow G_{\text{ini}} = 0$

Low \rightarrow (JDS) \rightarrow NO $\rightarrow G_{\text{ini}} = 0$

Right Node (Age > 30): JDS $\Rightarrow 3, 4, 5, 6, 7, 10$

$$\gamma=5, N=1, G_{\text{ini}} = 0.278$$

Income: High vs others $\Rightarrow G=0$

med & low can be split again

Med \rightarrow JDS (4, 10) $\rightarrow \gamma & \gamma, G=0$

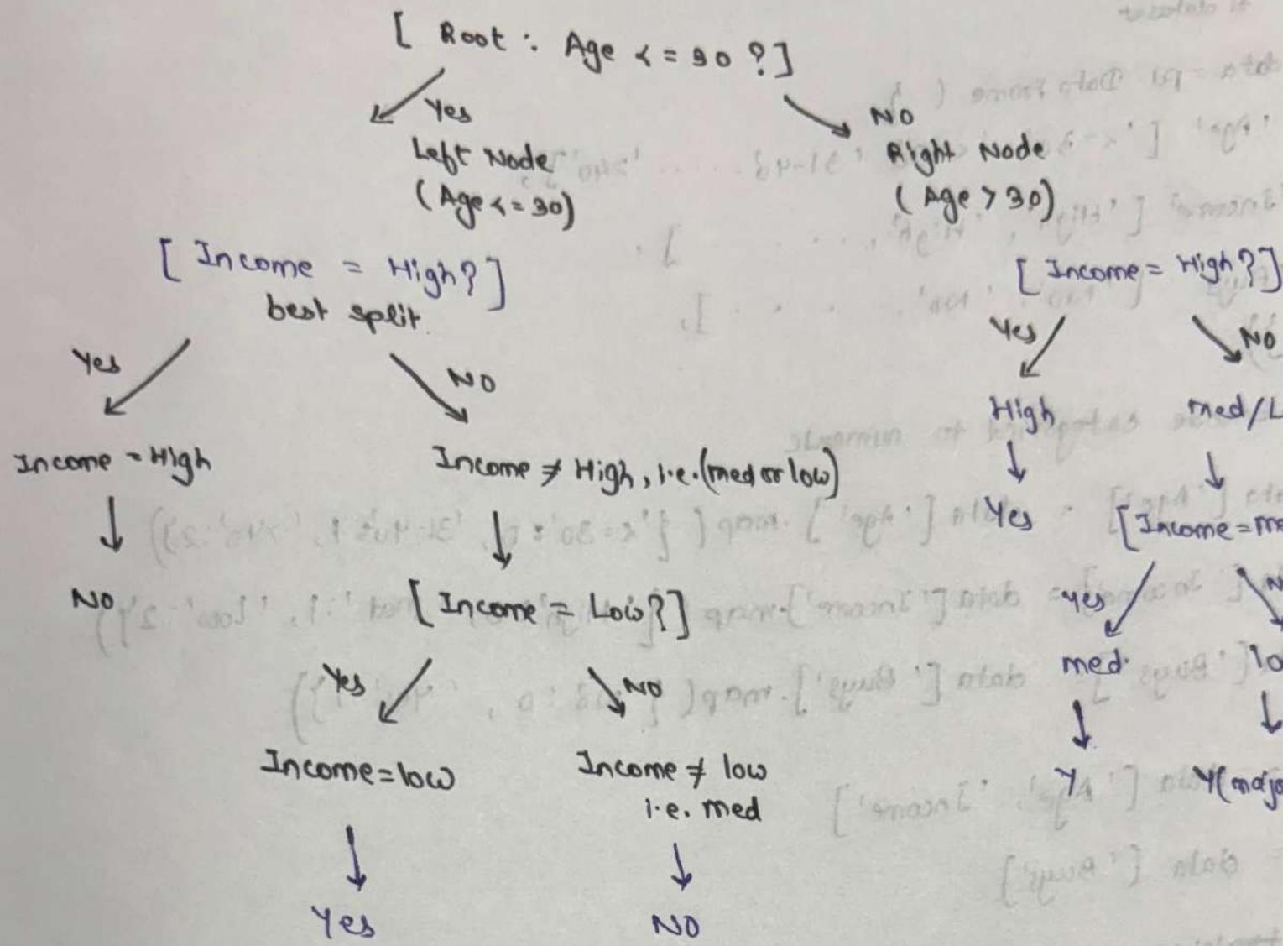
Low \rightarrow JDS (6, 7) $\rightarrow 21 & 1N, G=1 - \left(\left(\frac{2}{3}\right)^2 + \left(\frac{1}{3}\right)^2\right)$

$$1 - \left(\frac{4}{9} + \frac{1}{9}\right) \Rightarrow 0.44$$

Tree 1

Root Gini $\Rightarrow .48$

Root Node $\Rightarrow (\text{Age} \leq 30) ?$, lowest Gini gain



The same procedure goes on with other two trees as well
& finally, build a table as

ID	Tree 1	Tree 2	Tree 3	Majority
1	N	Y	N	N
2	N	Y	N	N
3	Y	Y	Y	Y