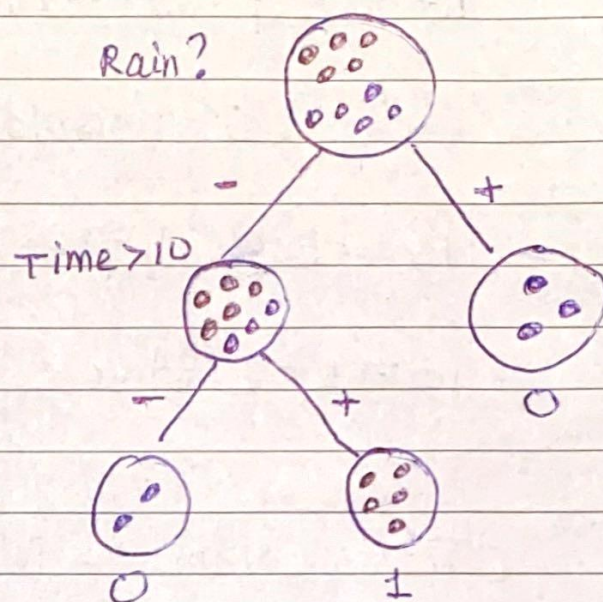


Implementing Decision Tree

Example: Person walking? or Taking a bus?

<u>Rain</u>	<u>Time</u>	<u>walk</u>
1	30	No
1	15	No
1	5	No
0	10	No
0	5	No
0	15	yes
0	20	yes
0	25	yes
0	30	yes
0	30	yes



- Time They have.
- The only thing that we have to find out is ~~where~~ at what which node we want to apply which question.
 - So why do we ask for rain at first & not for the time
 - & why do ask for time is greater than 10 &
 - why do not ~~ask~~ we as for if it's greater than 5 or greater than 20.
- The best split feature (value) (Threshold)
 - that we want to find out
 - At each node we want to find the best split value

• Entropy

$$E = - \sum P(x) \cdot \log_2(P(x))$$

$$P(x) = \frac{\#x}{n}$$

Example: $S = [0, 0, 0, 0, 0, 1, 1, 1, 1, 1]$

$$E = -\frac{5}{10} \log_2\left(\frac{5}{10}\right) - \frac{5}{10} \log_2\left(\frac{5}{10}\right) = -0.5 \log_2(0.5) - 0.5 \log_2(0.5)$$

$$E = -0.5 \cdot (-1) - 0.5 \cdot (-1) = 1$$

Information Gain

$$IG = E(\text{parent}) - [\text{weighted average}] \cdot E(\text{children})$$

Example: $S = [0, 0, 0, 0, 0, 1, 1, 1, 1, 1]$ $S_1 = [0, 0, 1, 1, 1, 1, 1]$, $S_2 = [0, 0, 0]$

$$IG = E(S) - \left[\left(\frac{7}{10} \right) \times E(S_1) + \left(\frac{3}{10} \right) \times E(S_2) \right]$$

$$IG = 1 - \left[\left(\frac{7}{10} \right) \times 0.863 + \left(\frac{3}{10} \right) \times 0 \right] = 0.395$$

Approach

• Train algorithm := Build the tree

1. Start at the top node & at each node select the best split based on the best information gain.
2. Greedy search: Loop over all features & over all thresholds (all possible feature values).
3. Save the best split feature & split threshold at each node.
4. Build the tree recursively.
5. Apply some stopping criteria to stop growing
e.g. here: maximum depth, minimum samples at node, no more class distribution in node.
6. When we have a leaf node, store the most common class label of this node.

• Predict := Traverse tree

7. Traverse the tree recursively.
8. At each node look at the best split feature of the test feature vector x & go left or right depending on $x[\text{feature_idx}] \leq \text{threshold}$
9. When we reach the leaf node we return the stored most common class label.