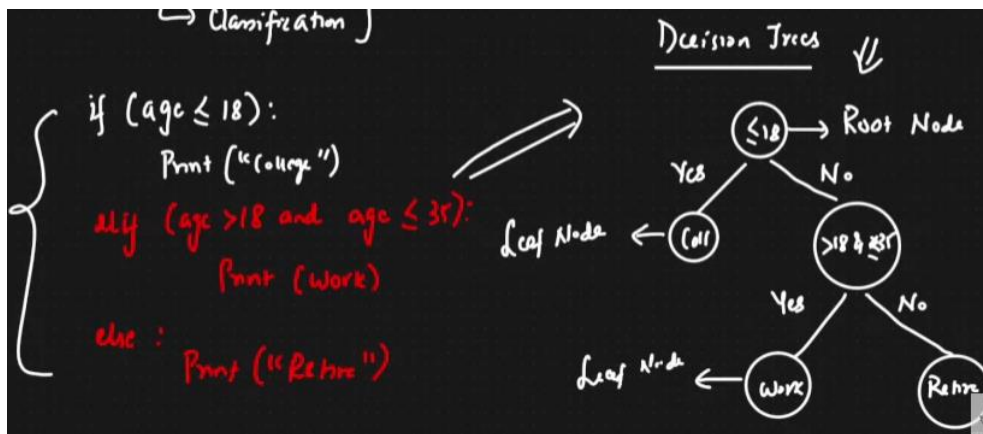
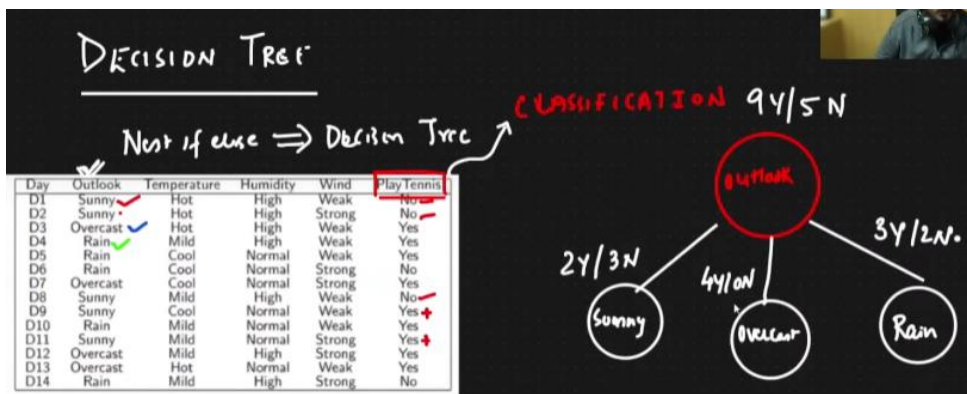


i) Decision Tree is like a flowchart of the python, if-else code!



ii) Classification: (here, outlook is randomly selected!)



a) How are the features selected? → through: Information Gain

Information Gain

Gain(S, f_i) = H(S) - ∑_{v ∈ Val} $\frac{|S_v|}{|S|} H(S_v)$

H(S)

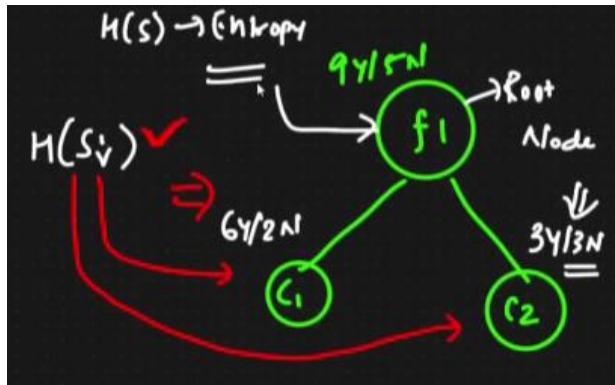
Were,

$H(S)$: Entropy of root node(f_1),

$H(S'|V)$: Entropy of c_1 & c_2 ,

$$\frac{SV}{S} : \left[\frac{\text{total } c_1}{\text{total } f_1} + \frac{\text{total } c_2}{\text{total } f_1} \right]$$

Example:



$$H(S) = -P_+ \log_2 P_+ - P_- \log_2 P_-$$

$$= -\frac{9}{14} \log_2 \left(\frac{9}{14}\right) - \frac{5}{14} \log_2 \left(\frac{5}{14}\right)$$

$$\approx \underline{\underline{0.94}}$$

$$H(c_1) = -\frac{6}{8} \log_2 \frac{6}{8} - \frac{2}{8} \log_2 \frac{2}{8}$$

$$\boxed{H(c_1) = 0.81} \quad \boxed{H(c_2) = 1}$$

$$\text{Gain}(S, f_1) = 0.94 - \left[\frac{8}{14} \times 0.81 + \frac{6}{14} \times 1 \right]$$

$$\text{Gain}(S, f_1) = \underline{\underline{0.049}}$$

$$\text{Gain}(S, f_1) = 0.049$$

$$\text{Gain}(S, f_2) = 0.051$$

Using which feature should I start splitting first

$\text{Gain}(S, f_2) >> \text{Gain}(S, f_1)$

1) we took root node as f_1 , found the $H(S)$ value.

2) went inside the f_1 's child root & found c_1 & c_2 .

3) we got all the necessary data, now we place the value in place of the formula.

4) we got: "Gain (S, f_1)"

5) similarly, find for other nodes (f_2, f_3, f_4 , etc.)

6) the node, having highest Gini value, is taken 1st!

b) Later, **Split** in 2 categories:

i) **Pure** (100% yes or 100% no): Overcast is the pure node, having 100% strike rate, 4 yes & 0 no!

ii) **Impure**: not a 100% strike rate!

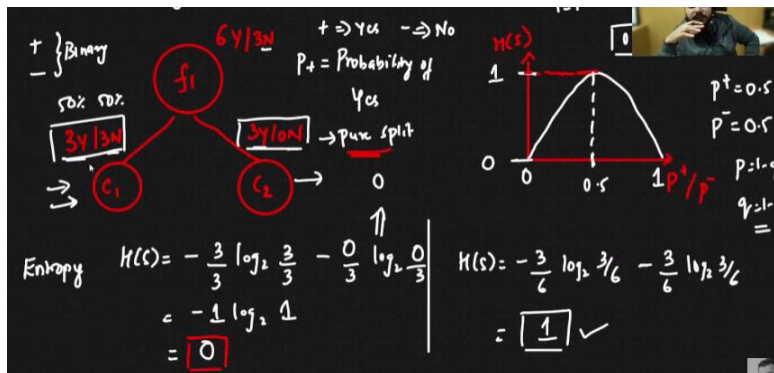
Once you get a pure node, stop else keep going on with the next features(columns)

c) How to know wheatear it's a **pure fit or impure fit?** → **Entropy or Gini Impurity**

i) **Entropy**:

$$H(S) = -P_+ \log_2 P_+ - P_- \log_2 P_- \quad \therefore \text{no, +: yes, } p_+ \text{: prob. of yes, } p_- \text{: prob. of no}$$

Example:



Entropy is always going to be between 0 to 1

0 = pure & 1 = impure

As you can see, at the right side we got $H(S) = 1$; split it further, taking other features/columns.

ii) **Gini Impurity/Coefficient**:

(*) **GINI Impurity** ✓

$$G.I = 1 - \sum_{i=1}^n (p_i)^2 \rightarrow$$

$$= 1 - [(p_+)^2 + (p_-)^2]$$

$$= 1 - \left[\left(\frac{1}{2}\right)^2 + \left(\frac{1}{2}\right)^2\right]$$

$$= 1 - \left[\frac{1}{2}\right] = \underline{\underline{0.5}}$$

n = 2 output { Yes No } 2Y/2N

1) took random no. of output, that's 2 each (yes & no)

2) placed the value inside the formula.

3) got the answer, 0.5 an impurity!

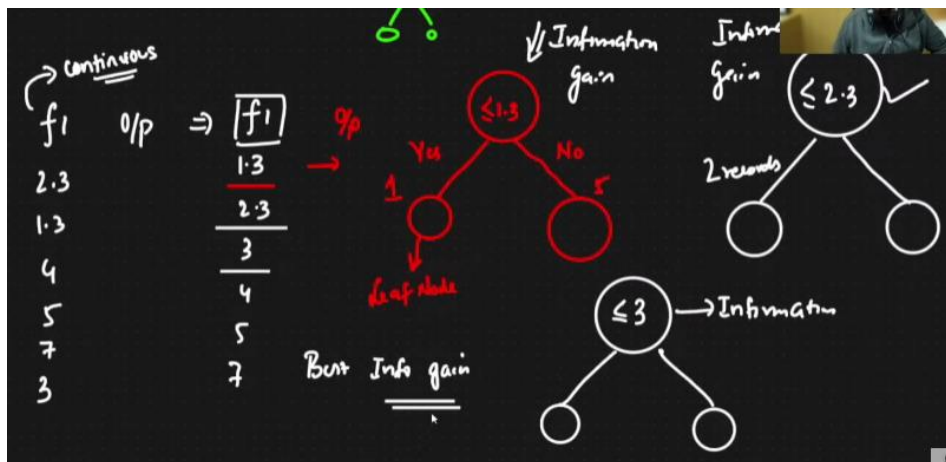
4) entropy has only 0 or 1 but Gini doesn't!

iii) Question may arise, which should be taken & when?

- ➔ When there's more than 100 nodes, take Gini, due to its simple maths & faster solution;
- ➔ As, entropy contains log & does takes lots of time!

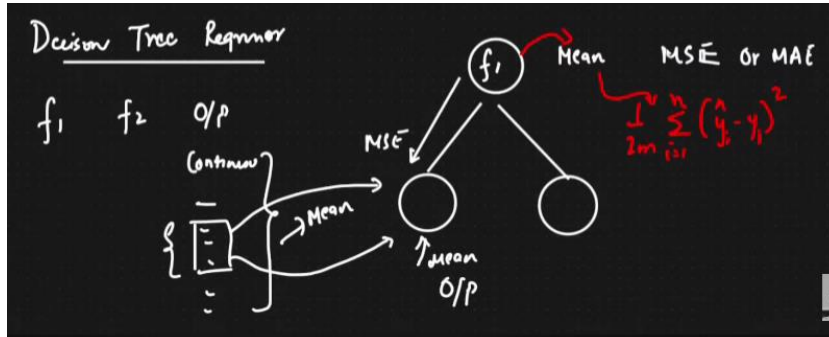
iii) Regression:

If we have 1 feature:



- Here, will first arrange the f_1 in ascending order
- Later, take the first value, that's 1.3 & find their information gain.
- Simultaneously, get information gain for all the remaining values & the one with highest will be taken to perform purity – impurity (entropy or Gini impurity)

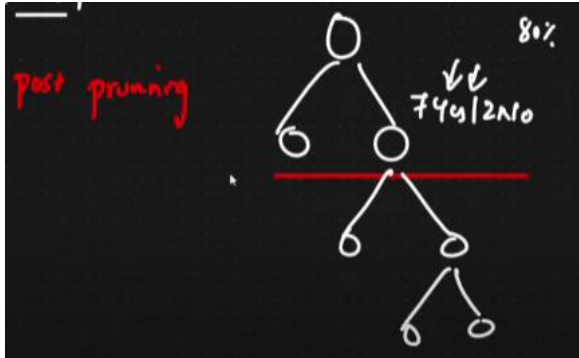
When we have multiple features:



- take all the mean of the output, will get assign to f_1 & will use MSE or MAE, instead of Entropy or Gini impurity
- based on the f_1 feature, assign the mean value & later find the MSE, MAE; in the end, split!
- during the split, some records will go under the f_1 , becoming c_1 , later find the mean of those value & find the mse or mae!
- as the mse gets reduced, that means we are reaching to leaf score!
- and the same thing will happen for c_2 .
- the mean value present at c_1 , c_2 , etc. will be the output!

iv) Hyperparameters:

Has **overfitting**, to fix this, will do: **post-pruning** & **pre-pruning**



If we know that, there's an 80% of a node to be yes; will cut the further part of the tree.

In the pre-pruning, will know the max_depth, max_leaf, we can get applying gridsearchcv.

Reference:

[1\) Decision Tree & Ensemble ML Algorithm](#)