PUNE INSTITUTE OF COMPUTER TECHNOLOGY

Subject: Machine Learning (LP-1 LAB)

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Assignment 3
Classification using Machine Learning

Problem Statement:

Perform the following operations on the given dataset:

A. Apply Data pre-processing (Label Encoding, Data Transformation…) techniques if necessary.
B. Perform data-preparation (Train-Test Split)
C. Apply Decision tree classification Algorithm
D. Evaluate Model.

Objective:

This assignment will help the students to realize how the decision tree classifier can be used and predictions using the same can be performed.

Theory:

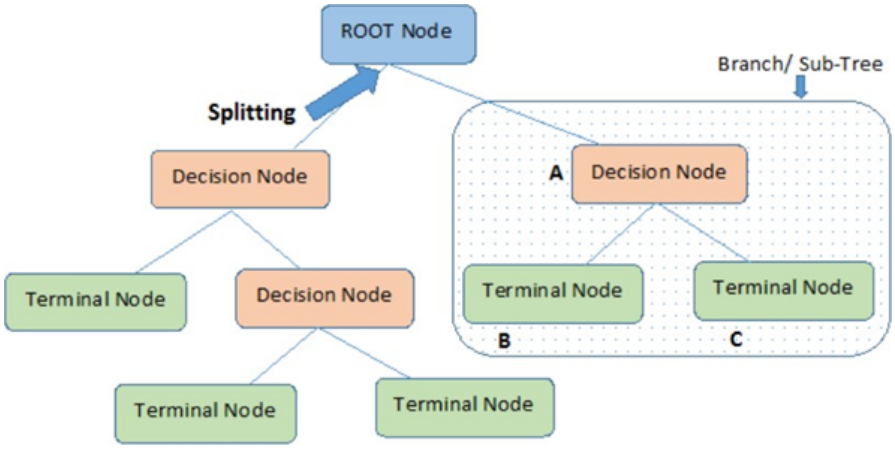
Classification:

1. Classification is the process of categorizing a given set of data into classes.
2. It can be performed on both structured or unstructured data.
3. The process starts with predicting the class of given data points.
4. The classes are often referred to as target, label or categories.

What is a Decision Tree?

It uses a flowchart like a tree structure to show the predictions that result from a series of feature-based splits.

It starts with a root node and ends with a decision made by leaves.



Root Nodes - It is the node present at the beginning of a decision tree. from this node, the population starts dividing according to various features.

Decision Nodes – the nodes we get after splitting the root nodes are called Decision Node

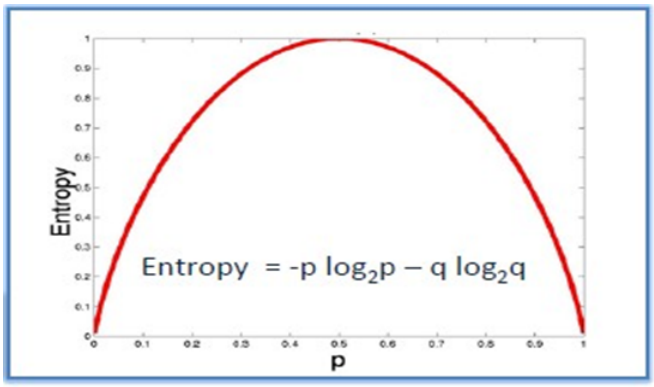
Leaf Nodes – the nodes where further splitting is not possible are called leaf nodes or terminal nodes

Sub-tree – just like a small portion of a graph is called sub-graph similarly a sub-section of this decision tree is called sub-tree.

Pruning – It is cutting down some nodes to stop overfitting.

Entropy:

Entropy is used to calculate the homogeneity of a sample. If the sample is completely homogeneous the entropy is zero and if the sample is equally divided it has an entropy of one.



Entropy = $-0.5 \log_2 0.5 - 0.5 \log_2 0.5 = 1$

a) Entropy using the frequency table of one attribute:

$$E(S) = \sum_{i=1}^{c} - p_i \log_2 p_i$$

Play Golf	
Yes	No
9	5

Entropy(PlayGolf) = Entropy (5,9)
= Entropy (0.36, 0.64)
= - (0.36 $\log_2$ 0.36) - (0.64 $\log_2$ 0.64)
= 0.94

b) Entropy using the frequency table of two attributes:

$$E(T, X) = \sum_{c \in X} P(c) E(c)$$

		Play Golf		
		Yes	No	
Outlook	Sunny	3	2	5
	Overcast	4	0	4
	Rainy	2	3	5
				14

E(PlayGolf, Outlook) = **P**(Sunny)***E**(3,2) + **P**(Overcast)***E**(4,0) + **P**(Rainy)***E**(2,3)
= (5/14)*0.971 + (4/14)*0.0 + (5/14)*0.971
= 0.693

Information Gain

The information gain is based on the decrease in entropy after a dataset is split on an attribute.

Constructing a decision tree is all about finding attributes that return the highest information gain (i.e., the most homogeneous branches).

Step 1: Calculate the entropy of the target.

Entropy(PlayGolf) = Entropy (5,9)

= Entropy (0.36, 0.64)

= - (0.36 $\log_2$ 0.36) - (0.64 $\log_2$ 0.64)

= 0.94

Step 2: The dataset is then split into different attributes. The entropy for each branch is calculated.

Then it is added proportionally, to get total entropy for the split. The resulting entropy is subtracted from the entropy before the split.

The result is the Information Gain or decrease in entropy.

		Play Golf	
		Yes	No
Outlook	Sunny	3	2
	Overcast	4	0
	Rainy	2	3
Gain = 0.247			

		Play Golf	
		Yes	No
Temp.	Hot	2	2
	Mild	4	2
	Cool	3	1
Gain = 0.029			

		Play Golf	
		Yes	No
Humidity	High	3	4
	Normal	6	1
Gain = 0.152			

		Play Golf	
		Yes	No
Windy	False	6	2
	True	3	3
Gain = 0.048			

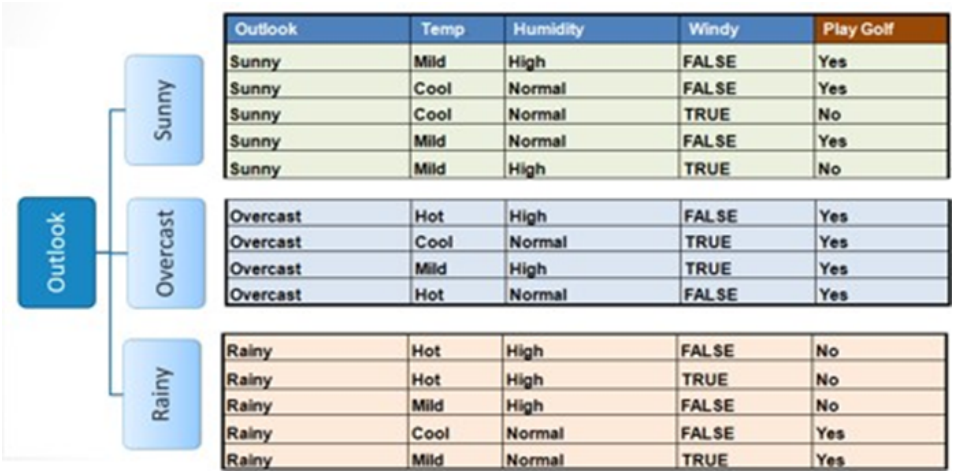
$$Gain(T, X) = Entropy(T) - Entropy(T, X)$$

G(PlayGolf, Outlook) = **E**(PlayGolf) – **E**(PlayGolf, Outlook)

= 0.940 – 0.693 = 0.247

Step 3: Choose the attribute with the largest information gain as the decision node, divide the dataset by its branches and repeat the same process on every branch.

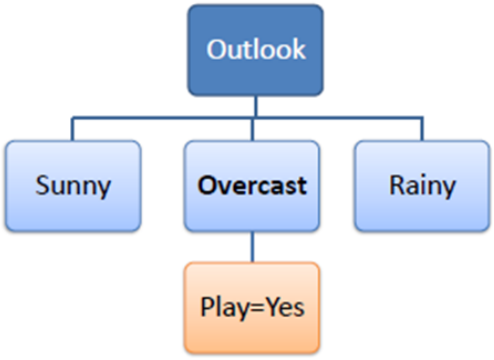
		Play Golf	
		Yes	No
Outlook	Sunny	3	2
	Overcast	4	0
	Rainy	2	3
Gain = 0.247			



Outlook	Temp	Humidity	Windy	Play Golf
Sunny	Mild	High	FALSE	Yes
Sunny	Cool	Normal	FALSE	Yes
Sunny	Cool	Normal	TRUE	No
Sunny	Mild	Normal	FALSE	Yes
Sunny	Mild	High	TRUE	No
Overcast	Hot	High	FALSE	Yes
Overcast	Cool	Normal	TRUE	Yes
Overcast	Mild	High	TRUE	Yes
Overcast	Hot	Normal	FALSE	Yes
Rainy	Hot	High	FALSE	No
Rainy	Hot	High	TRUE	No
Rainy	Mild	High	FALSE	No
Rainy	Cool	Normal	FALSE	Yes
Rainy	Mild	Normal	TRUE	Yes

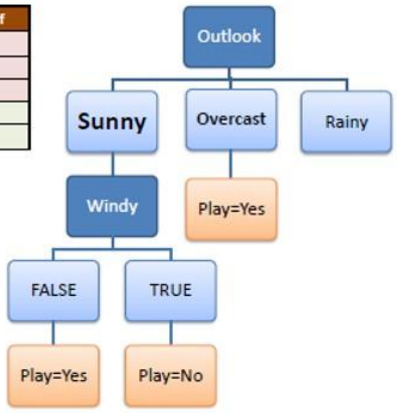
Step 4a: A branch with the entropy of 0 is a leaf node.

Temp	Humidity	Windy	Play Golf
Hot	High	FALSE	Yes
Cool	Normal	TRUE	Yes
Mild	High	TRUE	Yes
Hot	Normal	FALSE	Yes



Step 4b: A branch with an entropy of more than 0 needs further splitting.

Temp	Humidity	Windy	Play Golf
Mild	High	FALSE	Yes
Cool	Normal	FALSE	Yes
Mild	Normal	FALSE	Yes
Cool	Normal	TRUE	No
Mild	High	TRUE	No



Step 5: The ID3 algorithm is run recursively on the non-leaf branches until all data is classified.

Decision Tree to Decision Rules:

A decision tree can easily be transformed into a set of rules by mapping from the root node to the leaf nodes one by one.

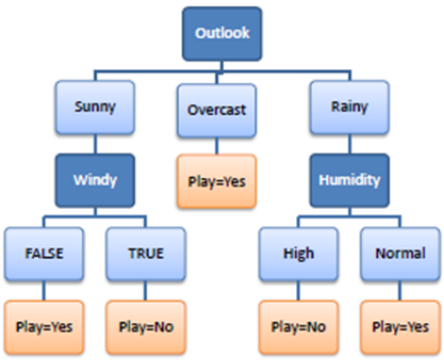
R_1: IF (Outlook=Sunny) AND (Windy=FALSE) THEN Play=Yes

R_2: IF (Outlook=Sunny) AND (Windy=TRUE) THEN Play=No

R_3: IF (Outlook=Overcast) THEN Play=Yes

R_4: IF (Outlook=Rainy) AND (Humidity=High) THEN Play=No

R_5: IF (Outlook=Rain) AND (Humidity=Normal) THEN Play=Yes



Pruning:

It is another method that can help us avoid overfitting. It helps in improving the performance of the tree by cutting the nodes or sub-nodes which are not significant. It removes the branches which have very low importance.

There are mainly 2 ways for pruning:

(i) **Pre-pruning** – we can stop growing the tree earlier, which means we can prune/remove/cut a node if it has low importance **while growing** the tree.

(ii)**Post-pruning** – once our **tree is built to its depth**, we can start pruning the nodes based on their significance.

Application:

Helpful in solving classification problems.

Conclusion:

Implemented classification algorithm on the given dataset and understood decision tree classifiers and how they are used for prediction.

Implementation: