Decision Tree Learning

Abdus Salam Azad

When should I
play Tennis ????

When should I play Tennis ????

Can You Give Me Some Examples !!!!!!!!

Classification

Day	Outlook	Temperature	Humidity	Wind	PlayTennis
D1	Sunny	Hot	High	Weak	No
D2	Sunny	Hot	High	Strong	No
D3	Overcast	Hot	High	Weak	Yes
D4	Rain	Mild	High	Weak	Yes
D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
D7	Overcast	Cool	Normal	Strong	Yes
D8	Sunny	Mild	High	Weak	No
D9	Sunny	Cool	Normal	Weak	Yes
D10	Rain	Mild	Normal	Weak	Yes
D11	Sunny	Mild	Normal	Strong	Yes
D12	Overcast	Mild	High	Strong	Yes
D13	Overcast	Hot	Normal	Weak	Yes
D14	Rain	Mild	High	Strong	No

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D6	Rain	Cool	Normal	Strong	No
D7	Overcast	Cool	Normal	Strong	Yes
D8	Sunny	Mild	High	Weak	No
D9	Sunny	Cool	Normal	Weak	Yes
D10	Rain	Mild	Normal	Weak	Yes
D11	Sunny	Mild	Normal	Strong	Yes
D12	Overcast	Mild	High	Strong	Yes
D13	Overcast	Hot	Normal	Weak	Yes
D14	Rain	Mild	High	Strong	No

Seems Like I really enjoy it when the outlook is overcast!!!!!

Day	Outl	nd	PlayTennis
D1	Sunny	Weak	No
			No
			Yes
			Yes
			Yes
			No
			Yes
			No
			Yes
			Yes
			Yes
			Yes
			Yes
			No

Classific

What About When
Its Sunny or
Raining ????

Day	Outlook	Temperature			
D1	Sunny	Hot			
D2	Sunny	Hot	High		
D3	Overcast				Yes
D4	Rain				Yes
D5	Rain				Yes
D6	Rain				No
D7	Overcast				Yes
D8	Sunny				No
D9	Sunny				Yes
D10	Rain				Yes
D11	Sunny				Yes
D12	Overcast	Mild	High	Strong	Yes
D13	Overcast	Hot	Normal	Weak	Yes
D14	Rain	Mild	High	Strong	No

Classification

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So, Its Humidity !!!!!!!!

How did we do that ?????

Classifi

I get it !!!
Its Recursion
!!!!!!!!!!!!!!!

Day	Outloo			l	PlayTenni
D1	Sunny			k	No
D2	Sunny			g	No
D8	Sunny			k	No
D9	Sunny			k	Yes
D11	Sunny		Normal	Strong	Yes

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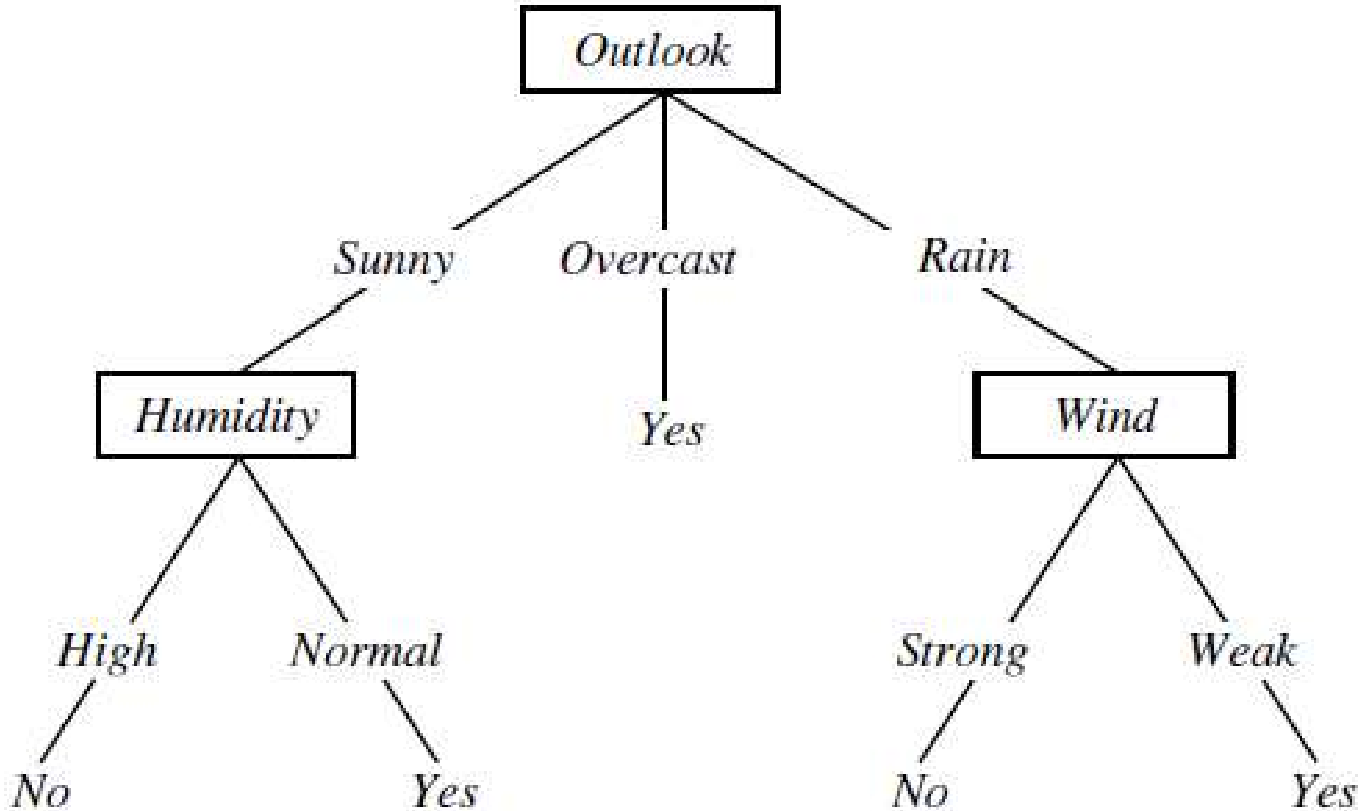
All days here are sunny, so whats the point keeping it !!!!!!!!!

Day	Outlook	Temperature	Humidity	Wind	PlayTennis
D4	Rain	Mild	High	Weak	Yes
D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
D14	Rain	Mild	High	Strong	No

Day	Outlook	Temperature	Humidity	Wind	PlayTennis
D4	Rain	Mild	High	Weak	Yes
D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
D14	Rain	Mild	High	Strong	No

Its Wind !

Learned Tree for Prediction




Thank you BUET CSE!!!!!!

ID3($Examples$, $Target\_attribute$, $Attributes$)

Examples are the training examples. Target_attribute is the attribute whose value is to be predicted by the tree. Attributes is a list of other attributes that may be tested by the learned decision tree. Returns a decision tree that correctly classifies the given Examples.

- Create a *Root* node for the tree
- If all *Examples* are positive, Return the single-node tree *Root*, with label = +
- If all *Examples* are negative, Return the single-node tree *Root*, with label = −
- If *Attributes* is empty, Return the single-node tree *Root*, with label = most common value of *Target_attribute* in *Examples*
- Otherwise Begin
    - $A \leftarrow$ the attribute from *Attributes* that best* classifies *Examples*
    - The decision attribute for *Root* $\leftarrow A$
    - For each possible value, v_i, of A,
        - Add a new tree branch below *Root*, corresponding to the test $A = v_i$
        - Let $Examples_{v_i}$ be the subset of *Examples* that have value v_i for A
        - If $Examples_{v_i}$ is empty
            - Then below this new branch add a leaf node with label = most common value of *Target_attribute* in *Examples*
            - Else below this new branch add the subtree
              ID3($Examples_{v_i}$, $Target\_attribute$, $Attributes - \{A\}$))
- End
- Return *Root*

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ID3(*Examples*, *Target_att*
Examples are th ... *be*
predicted by the ... *ed*
decision tree. Re

- How to choose the BEST ???
- More importantly what is the BEST ????

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Entropy

- S is a sample of training examples
- $p_{\oplus}$ is the proportion of positive examples in S
- $p_{\ominus}$ is the proportion of negative examples in S
- Entropy measures the impurity of S

$$Entropy(S) \equiv -p_{\oplus} \log_2 p_{\oplus} - p_{\ominus} \log_2 p_{\ominus}$$

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- Entropy Is **Zero (Minimum)**, When all the examples belong to **same class**!!!
- Entropy Is **1(Maximum)**, When there are **equal** number of positive and negative examples!

Entropy

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To illustrate, suppose S is a collection of 14 examples of some boolean concept, including 9 positive and 5 negative examples (we adopt the notation $[9+, 5-]$ to summarize such a sample of data). Then the entropy of S relative to this boolean classification is

$$\begin{aligned} Entropy([9+, 5-]) &= -(9/14)\log_2(9/14) - (5/14)\log_2(5/14) \\ &= 0.940 \end{aligned} \tag{3.2}$$

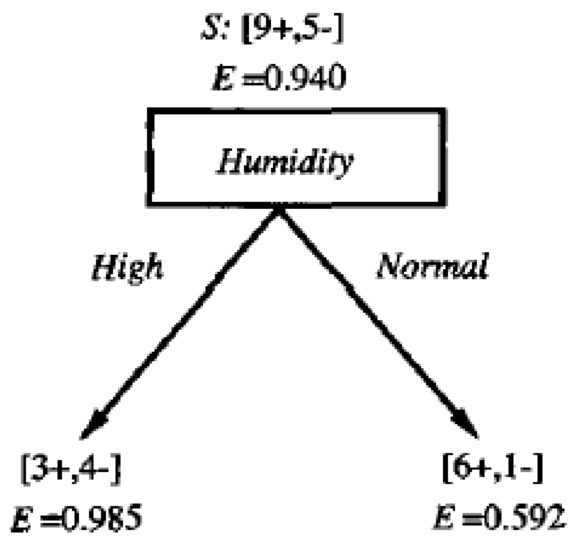
$$Entropy(S) \equiv \sum_{i=1}^{c} -p_i \log_2 p_i$$

Information Gain

$$Gain(S, A) \equiv Entropy(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} Entropy(S_v)$$

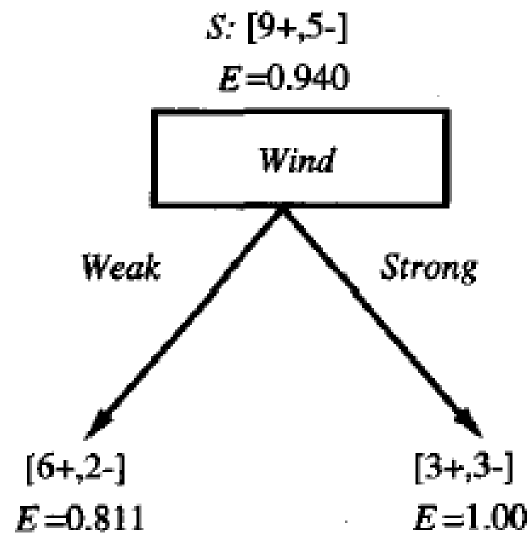
$$\begin{aligned}
Values(Wind) &= Weak, Strong \\
S &= [9+, 5-] \\
S_{Weak} &\leftarrow [6+, 2-] \\
S_{Strong} &\leftarrow [3+, 3-] \\
Gain(S, Wind) &= Entropy(S) - \sum_{v \in \{Weak, Strong\}} \frac{|S_v|}{|S|} Entropy(S_v) \\
&= Entropy(S) - (8/14) Entropy(S_{Weak}) \\
&\quad - (6/14) Entropy(S_{Strong}) \\
&= 0.940 - (8/14)0.811 - (6/14)1.00 \\
&= 0.048
\end{aligned}$$

Which attribute is the best classifier?



Gain (S, Humidity)

= .940 - (7/14).985 - (7/14).592
= .151



Gain (S, Wind)

= .940 - (8/14).811 - (6/14)1.0
= .048

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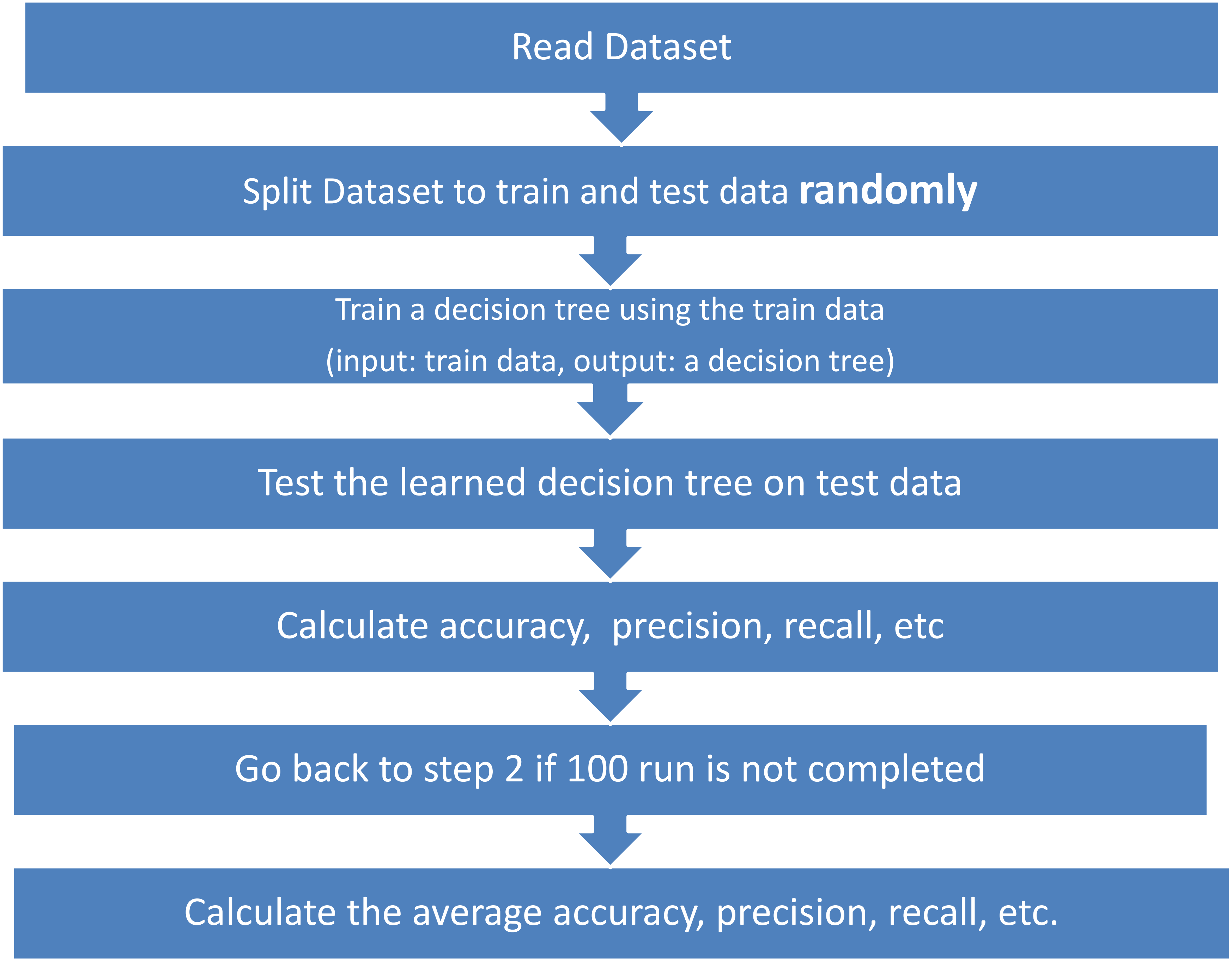
$$Gain(S, Outlook) = 0.246$$

$$Gain(S, Humidity) = 0.151$$

$$Gain(S, Wind) = 0.048$$

$$Gain(S, Temperature) = 0.029$$


Read Dataset
Split Dataset to train and test data **randomly**
Train a decision tree using the train data
(input: train data, output: a decision tree)
Test the learned decision tree on test data
Calculate accuracy, precision, recall, etc
Go back to step 2 if 100 run is not completed
Calculate the average accuracy, precision, recall, etc.

Measuring Performance

		Predicted class		Total instances
		+	−	
Actual class	+	TP	FN	P
	−	FP	TN	N

TP: true positives
The number of positive instances that are classified as positive

FP: false positives
The number of negative instances that are classified as positive

FN: false negatives
The number of positive instances that are classified as negative

TN: true negatives
The number of negative instances that are classified as negative

P = TP + FN
The total number of positive instances

N = FP + TN
The total number of negative instances

Why Reduce Entropy
???

How & Why am I preferring shorter trees ?

Does it take me to the global optimum ???

Why didn’t I just classify over the attribute “Day” ???

Why different performance metric ???