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Institut Informatika & Bisnis Darmajaya

Kampus Merdeka INDONESIA JAYA

MERDEKA BELAJAR

DATA SCIENCE DARMAJAYA
"YOUR BEST FUTURE IN DATA"

MEETING: [6]

DECISION TREE / IDE3

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Decision Tree: Outline

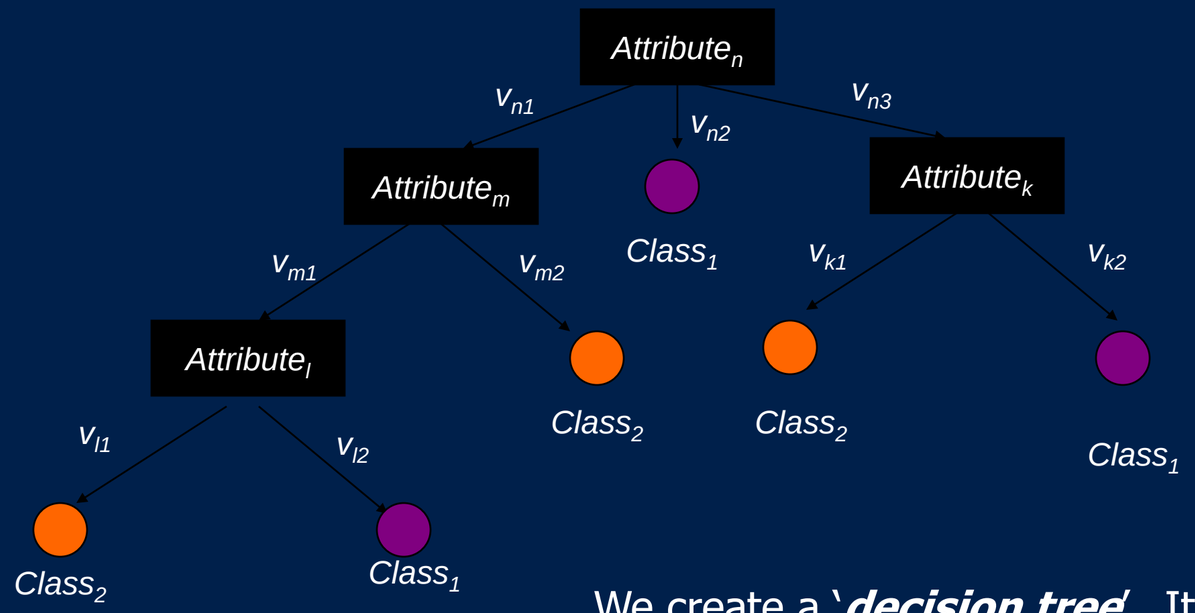
- Decision tree representation
- ID3 learning algorithm
- Entropy, information gain
- Overfitting

Defining the Task

- Imagine we've got a set of data containing several types, or ***classes***.
  - E.g. information about customers, and class=whether or not they buy anything.

- Can we predict, i.e ***classify***, whether a previously unseen customer will buy something?

An Example Decision Tree



We create a '***decision tree***'. It acts like a function that can predict and output given an input

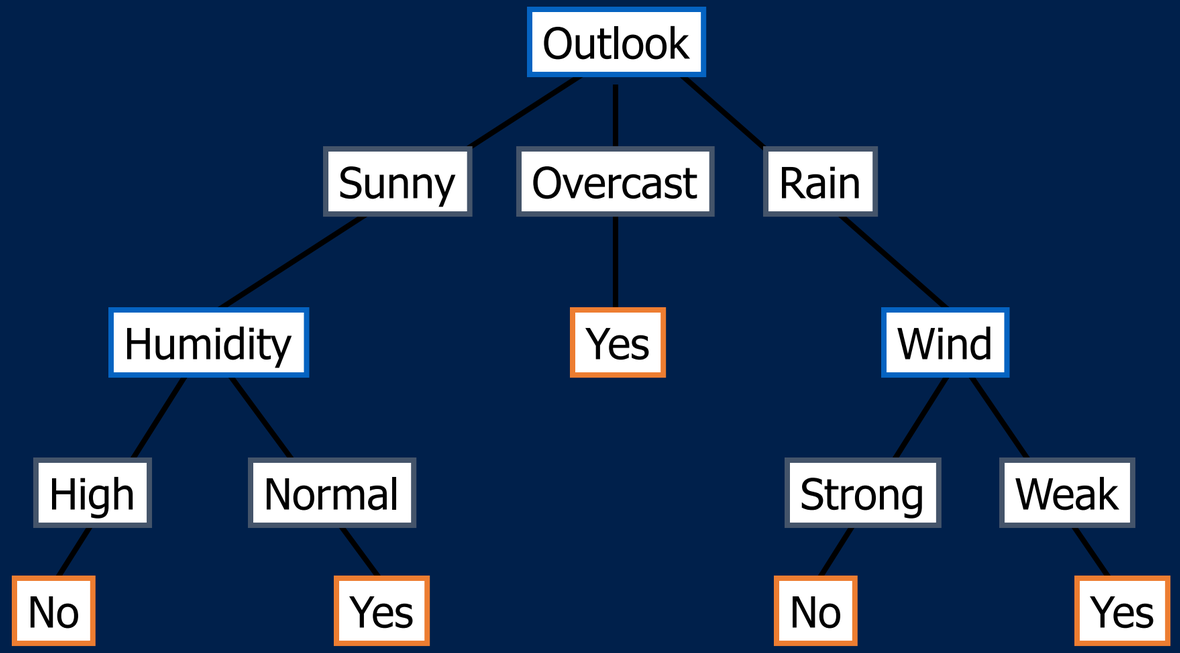
Decision Trees

- The idea is to ***ask a series of questions***, starting at the root, that will lead to a leaf node.
- The ***leaf node provides the classification***.

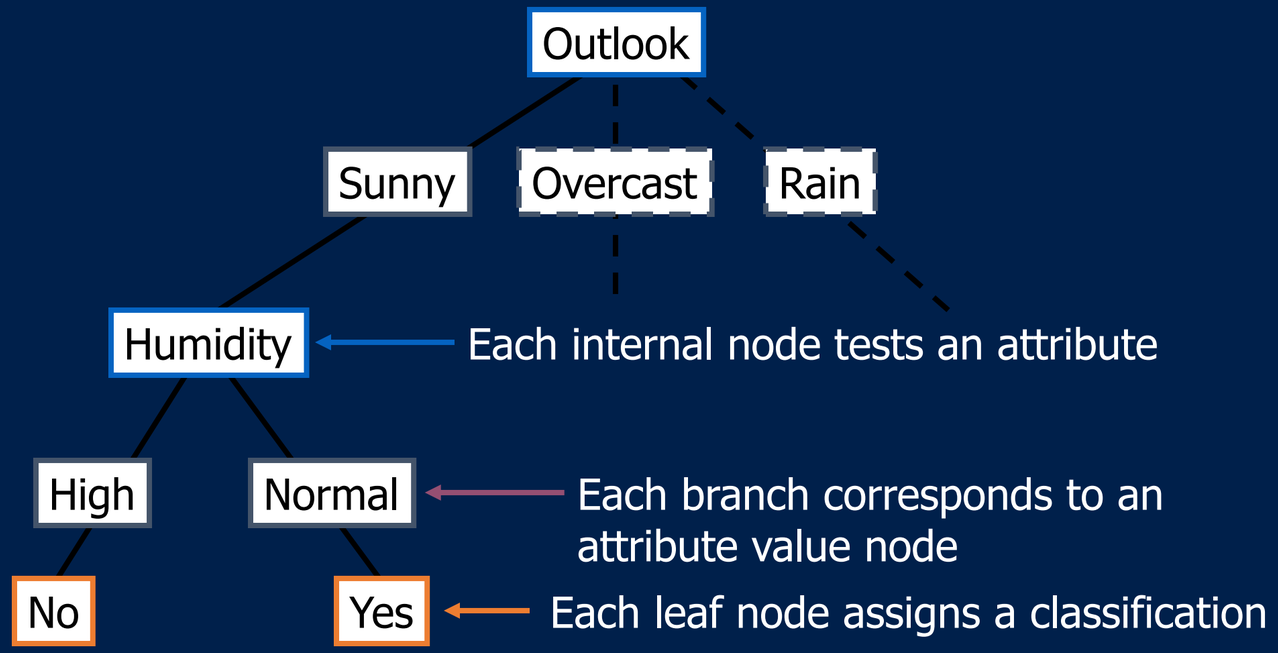
Classification by Decision Tree Induction

- Decision tree
  - A flow-chart-like tree structure
  - Internal node denotes a test on an attribute
  - Branch represents an outcome of the test
  - Leaf nodes represent class labels or class distribution
- Decision tree generation consists of two phases
  - Tree construction
    - At start, all the training examples are at the root
    - Partition examples recursively based on selected attributes
  - Tree pruning
    - Identify and remove branches that reflect noise or outliers
- Once the tree is build
  - Use of decision tree: Classifying an unknown sample

Decision Tree for PlayTennis

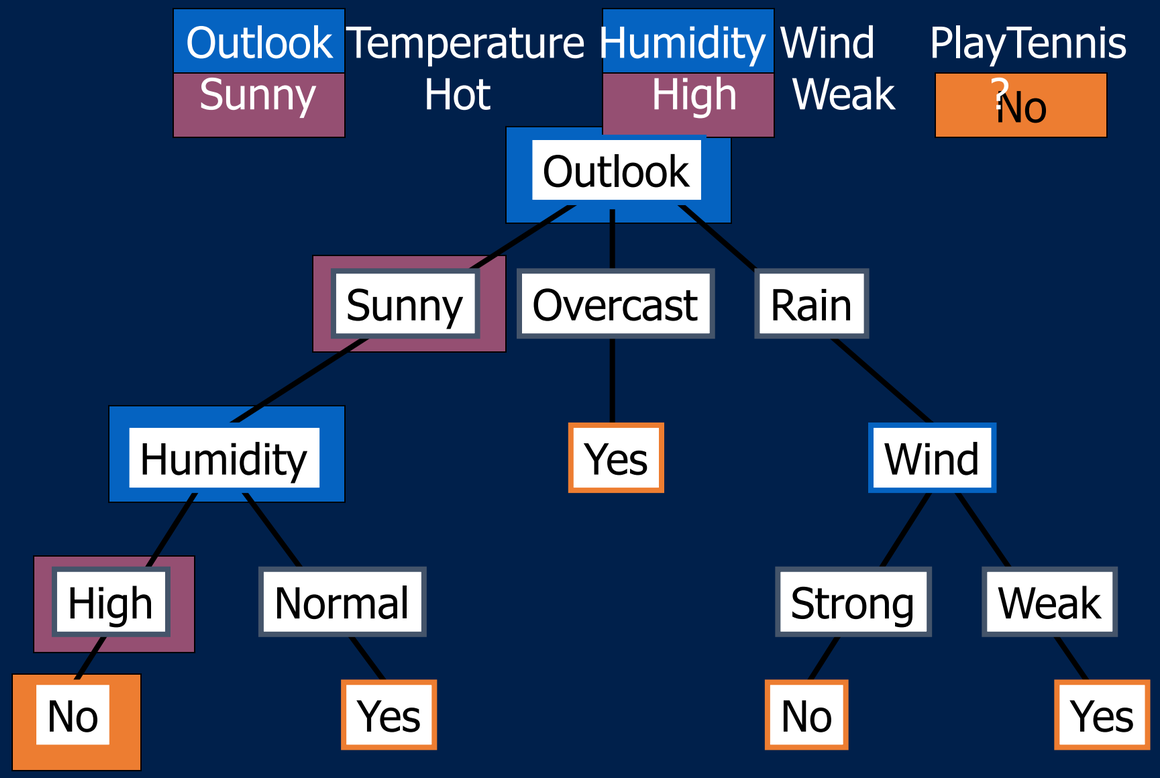


Decision Tree for PlayTennis



Decision Tre for PlayTennis

Outlook	Temperature	Humidity	Wind	PlayTennis
Sunny	Hot	High	Weak	No



Decision Trees

Consider these data:

A number of examples of weather, for several days, with a classification 'PlayTennis.'

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

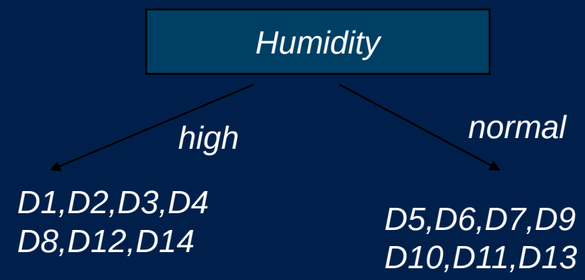
Decision Tree Algorithm

Building a decision tree

1. Select an attribute
2. Create the subsets of the example data for each value of the attribute
3. For each subset
   - *if not all the elements of the subset belongs to same class repeat the steps 1-3 for the subset*

Building Decision Trees

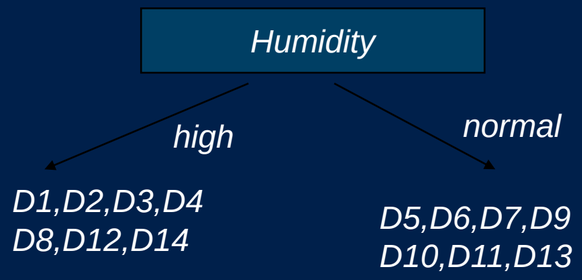
*Let's start building the tree from scratch. We first need to decide which attribute to make a decision. Let's say we selected "**humidity**"*



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

Building Decision Trees

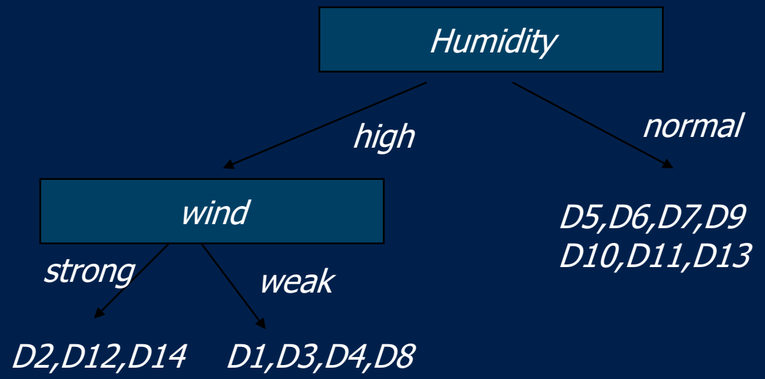
*Now lets classify the first subset D1,D2,D3,D4,D8,D12,D14 using attribute "**wind**"*



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
D8	Sunny	Mild	High	Weak	No
D12	Overcast	Mild	High	Strong	Yes
D14	Rain	Mild	High	Strong	No

Building Decision Trees

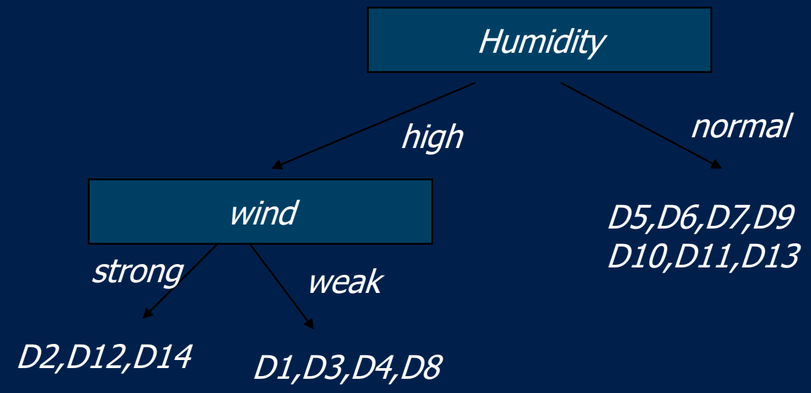
*Subset D1,D2,D3,D4,D8,D12,D14 classified by attribute "**wind**"*



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
D8	Sunny	Mild	High	Weak	No
D12	Overcast	Mild	High	Strong	Yes
D14	Rain	Mild	High	Strong	No

Building Decision Trees

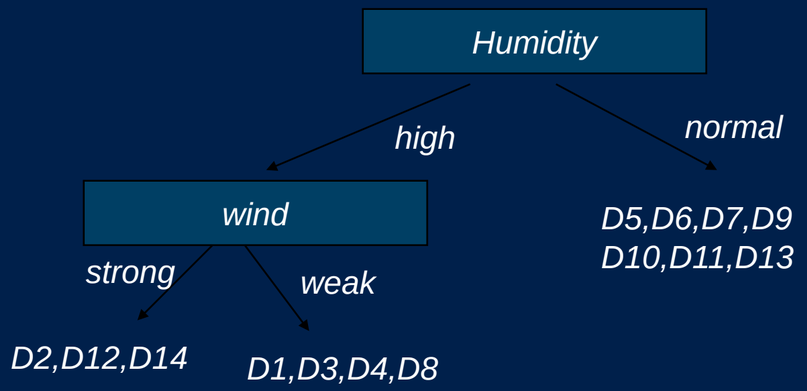
Now lets classify the subset D2,D12,D14 using attribute ***"outlook"***



Day	Outlook	Temperature	Humidity	Wind	PlayTennis
D2	Sunny	Hot	High	Strong	No
D12	Overcast	Mild	High	Strong	Yes
D14	Rain	Mild	High	Strong	No

Building Decision Trees

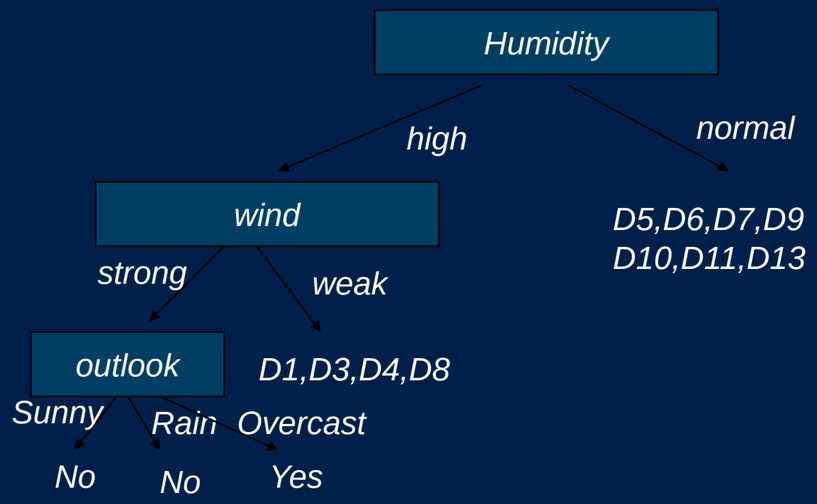
*Subset D2,D12,D14 classified by "**outlook**"*



Day	Outlook	Temperature	Humidity	Wind	PlayTennis
D2	Sunny	Hot	High	Strong	No
D12	Overcast	Mild	High	Strong	Yes
D14	Rain	Mild	High	Strong	No

Building Decision Trees

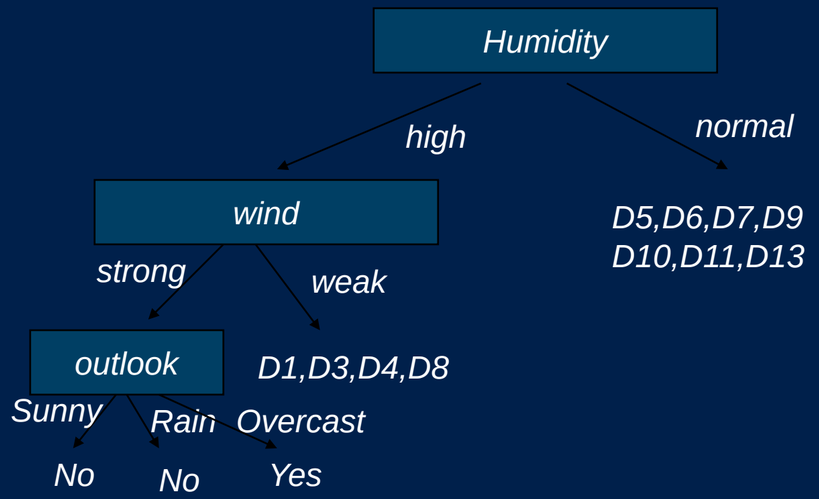
*subset D2,D12,D14 classified using attribute "**outlook**"*



Day	Outlook	Temperature	Humidity	Wind	PlayTennis
D2	Sunny	Hot	High	Strong	No
D12	Overcast	Mild	High	Strong	Yes
D14	Rain	Mild	High	Strong	No

Building Decision Trees

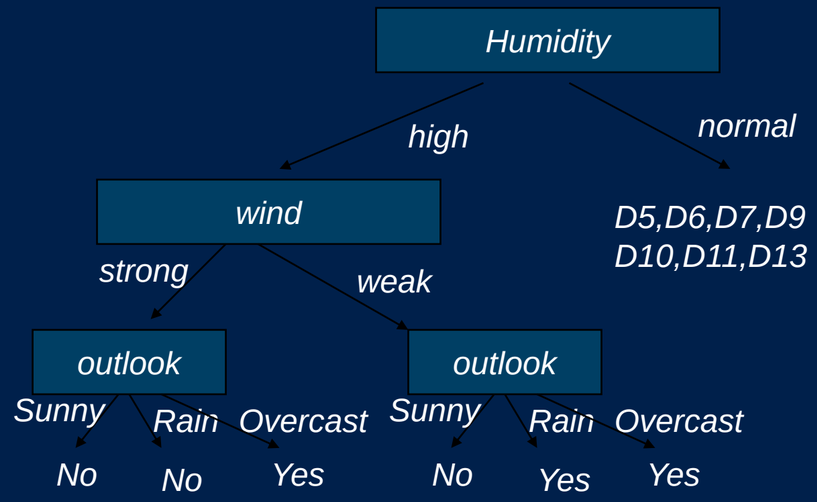
*Now lets classify the subset D1,D3,D4,D8 using attribute "**outlook**"*



Day	Outlook	Temperature	Humidity	Wind	PlayTennis
D1	Sunny	Hot	High	Weak	No
D3	Overcast	Hot	High	Weak	Yes
D4	Rain	Mild	High	Weak	Yes
D8	Sunny	Mild	High	Weak	No

Building Decision Trees

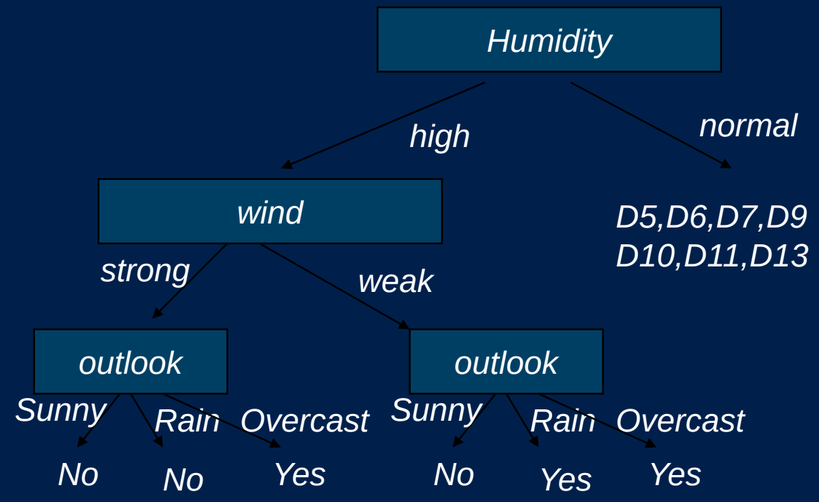
*subset D1,D3,D4,D8 classified by "**outlook**"*



Day	Outlook	Temperature	Humidity	Wind	PlayTennis
D1	Sunny	Hot	High	Weak	No
D3	Overcast	Hot	High	Weak	Yes
D4	Rain	Mild	High	Weak	Yes
D8	Sunny	Mild	High	Weak	No

Building Decision Trees

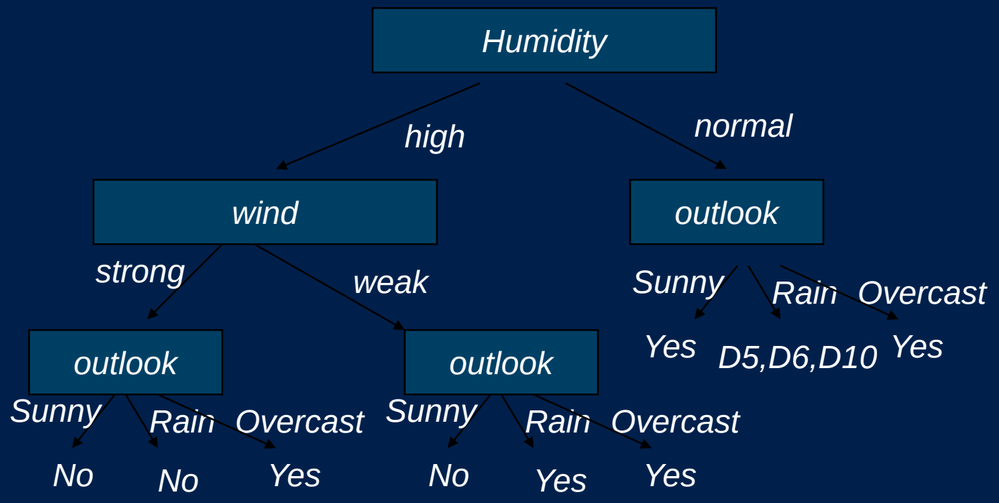
*Now classify the subset D5,D6,D7,D9,D10,D11,D13 using attribute "**outlook**"*



Day	Outlook	Temperature	Humidity	Wind	PlayTennis
D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
D7	Overcast	Cool	Normal	Strong	Yes
D9	Sunny	Cool	Normal	Weak	Yes
D10	Rain	Mild	Normal	Weak	Yes
D11	Sunny	Mild	Normal	Strong	Yes
D13	Overcast	Hot	Normal	Weak	Yes

Building Decision Trees

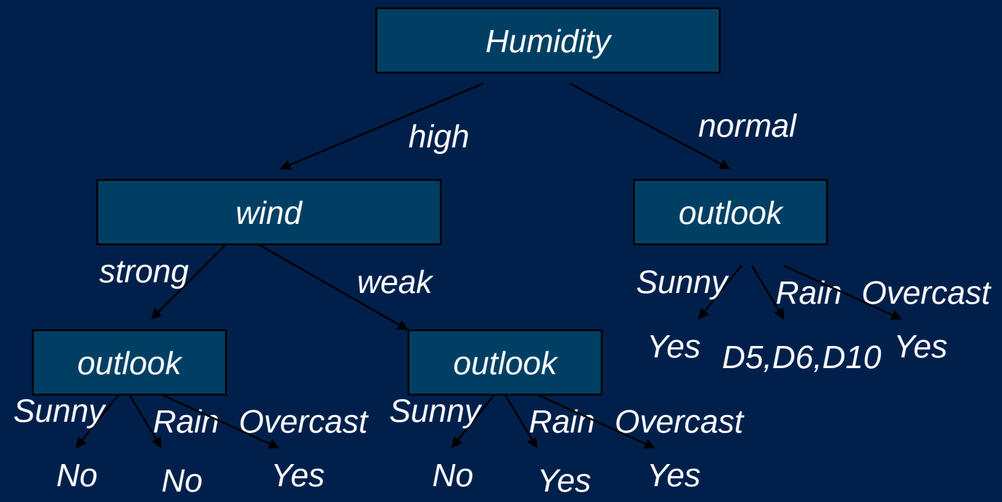
subset D5,D6,D7,D9,D10,D11,D13
*classified by "**outlook**"*



Day	Outlook	Temperature	Humidity	Wind	PlayTennis
D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
D7	Overcast	Cool	Normal	Strong	Yes
D9	Sunny	Cool	Normal	Weak	Yes
D10	Rain	Mild	Normal	Weak	Yes
D11	Sunny	Mild	Normal	Strong	Yes
D13	Overcast	Hot	Normal	Weak	Yes

Building Decision Trees

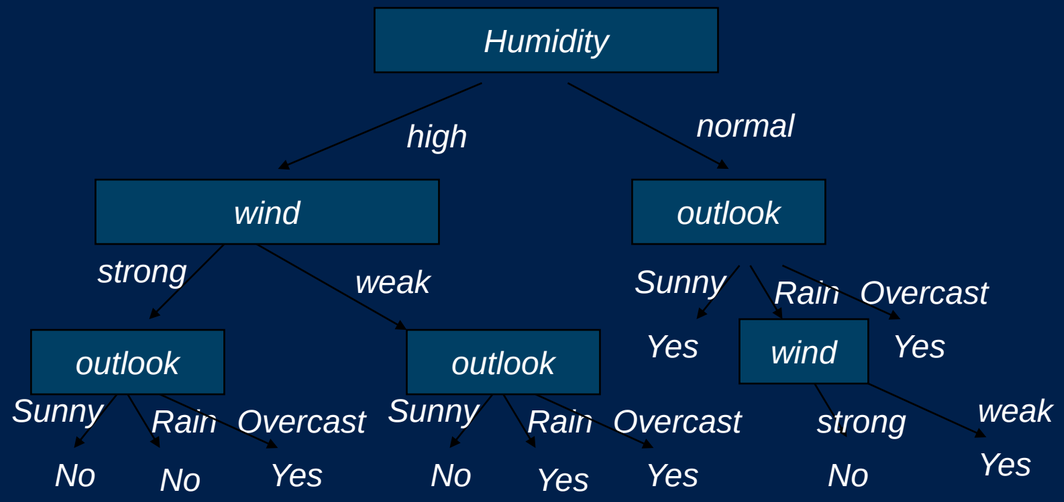
*Finally classify subset D5,D6,D10by "**wind**"*



Day	Outlook	Temperature	Humidity	Wind	PlayTennis
D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
D10	Rain	Mild	Normal	Weak	Yes

Building Decision Trees

*subset D5,D6,D10 classified by "**wind**"*

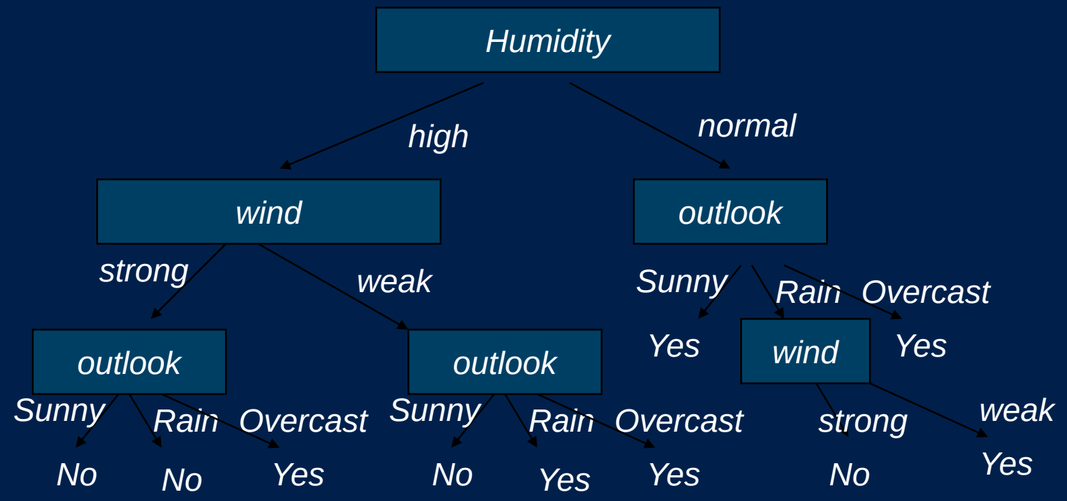


Day	Outlook	Temperature	Humidity	Wind	PlayTennis
D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
D10	Rain	Mild	Normal	Weak	Yes

Decision Trees and Logic

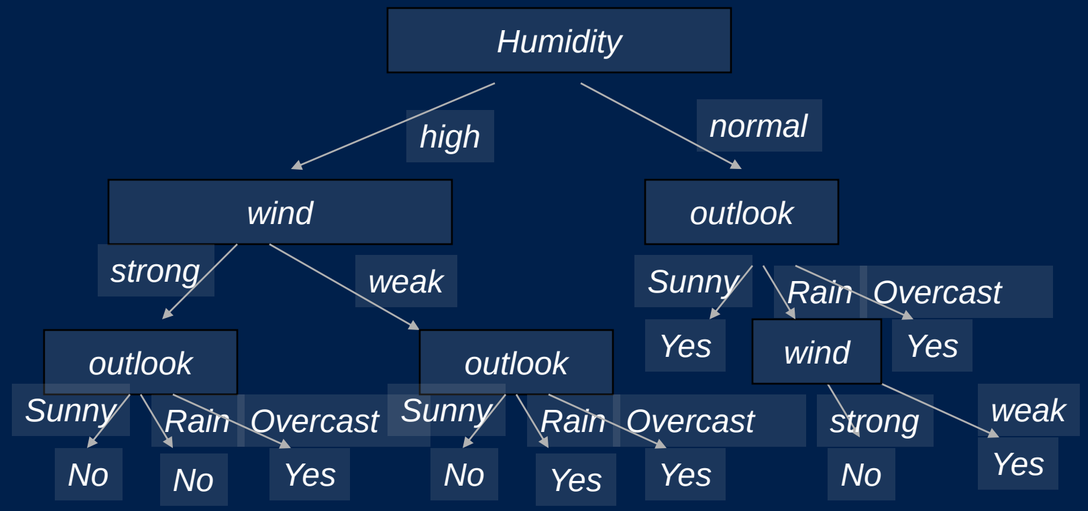
The decision tree can be expressed as an expression or if-then-else sentences:

(humidity=high $\wedge$ wind=strong $\wedge$ outlook=overcast) $\vee$
(humidity=high $\wedge$ wind=weak $\wedge$ outlook=overcast) $\vee$
(humidity=normal $\wedge$ outlook=sunny) $\vee$
(humidity=normal $\wedge$ outlook=overcast) $\vee$
(humidity=normal $\wedge$ outlook=rain $\wedge$ wind=weak) $\Rightarrow$ 'Yes'



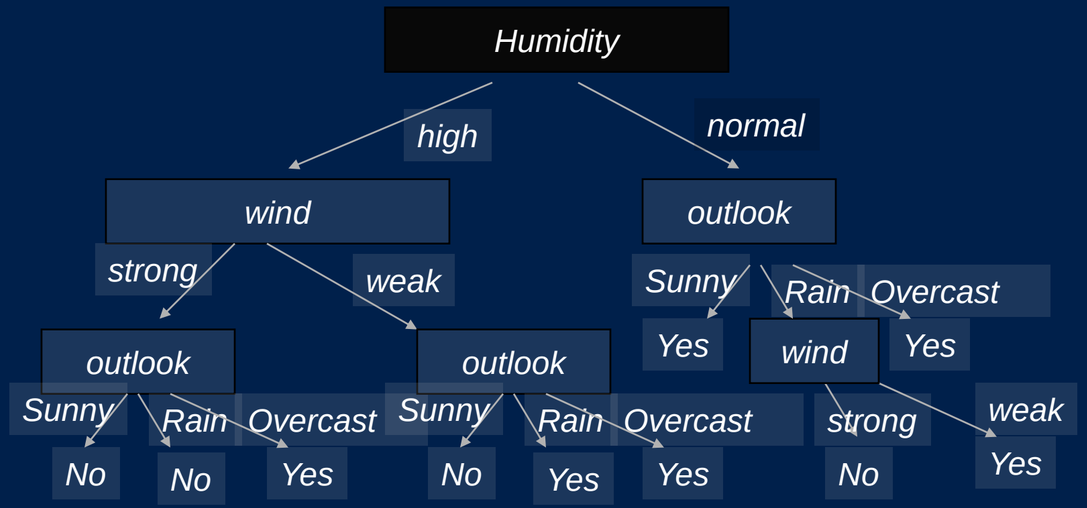
Using Decision Trees

Now let's classify an unseen example: <sunny,hot,normal,weak>=?



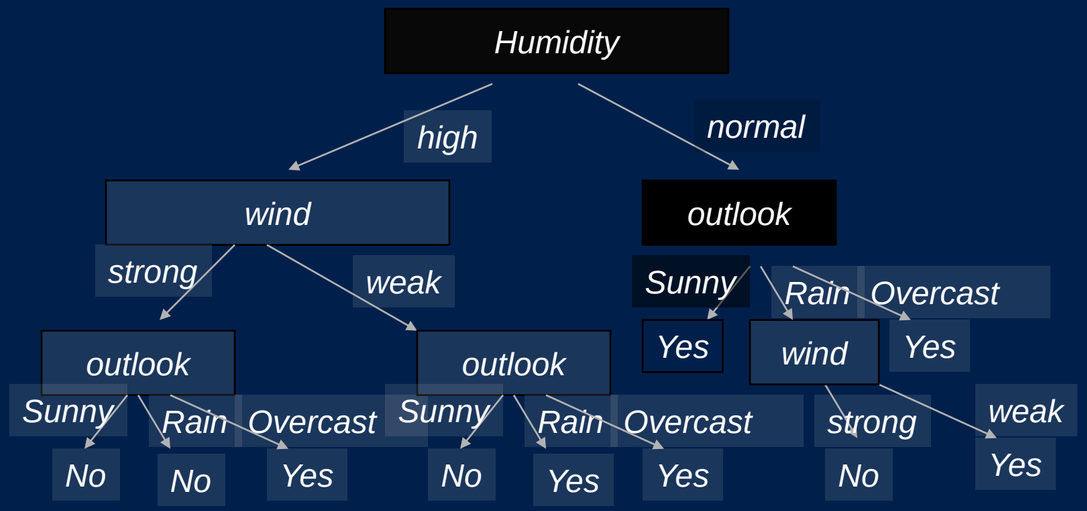
Using Decision Trees

Classifying: <sunny,hot,normal,weak>=?



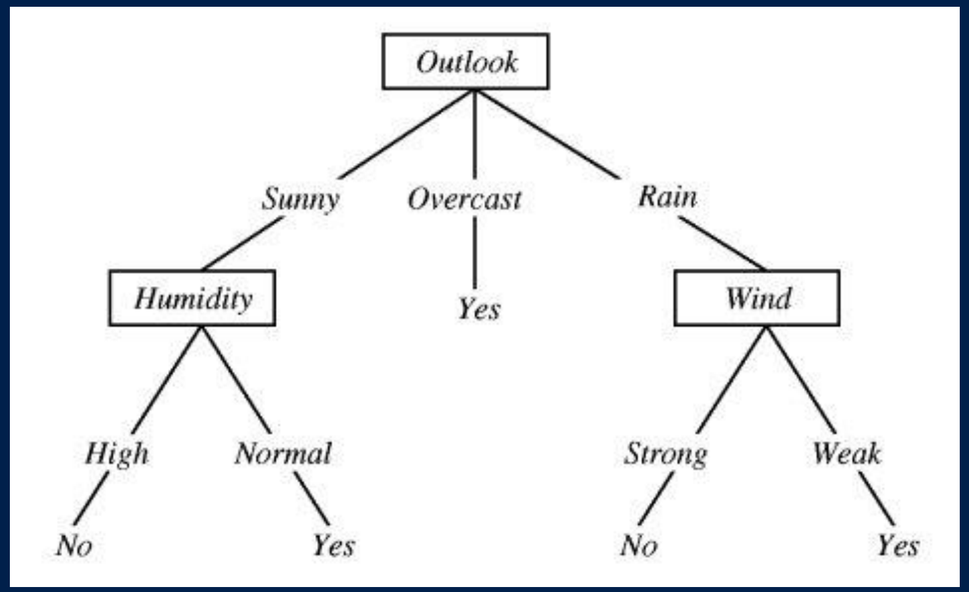
Using Decision Trees

Classification for: <sunny,hot,normal,weak>=Yes



A Big Problem…

Here's another tree from the ***same training data*** that has a different attribute order:



Which attribute should we choose for each branch?

Choosing Attributes

- We need a way of ***choosing the best attribute*** each time we add a node to the tree.
- Most commonly we use a measure called ***entropy***.
- Entropy measure the degree of ***disorder*** in a set of objects.

Entropy

- In our system we have
  - 9 positive examples
  - 5 negative examples

- The ***entropy, E(S),*** of a set of examples is:
  - $E(S) = \sum_{i=1}^{c} -p_i \log p_i$
  - Where c = no of classes and p_i = ratio of the number of examples of this value over the total number of examples.

- P+ = 9/14
- P- = 5/14
- E = - 9/14 $\log_2$ 9/14 - 5/14 $\log_2$ 5/14
- E = 0.940

- In a ***homogenous*** (totally ordered) system, the entropy is 0.

- In a ***totally heterogeneous*** system (totally disordered), all classes have equal numbers of instances; the entropy is 1

Entropy

- We can evaluate ***each attribute*** for their entropy.
  - E.g. evaluate the attribute "*Temperature*"
  - Three values: 'Hot', 'Mild', 'Cool.'
- So we have three subsets, one for each value of 'Temperature'.

S_{hot}={D1,D2,D3,D13}

S_{mild}={D4,D8,D10,D11,D12,D14}

S_{cool}={D5,D6,D7,D9}

We will now find:

$E(S_{hot})$
$E(S_{mild})$
$E(S_{cool})$

Entropy

S_{hot}= {D1,D2,D3,D13}

Examples:
2 positive
2 negative

Totally heterogeneous + disordered therefore:
$p_+ = 0.5$
$p_- = 0.5$

$Entropy(S_{hot}) = -0.5\log_2 0.5 - 0.5\log_2 0.5 = \mathbf{1.0}$

S_{mild}= {D4,D8,D10, D11,D12,D14}

Examples:
4 positive
2 negative

Proportions of each class in this subset:
$p_+ = 0.666$
$p_- = 0.333$

$Entropy(S_{mild}) = -0.666\log_2 0.666 - 0.333\log_2 0.333 = \mathbf{0.918}$

S_{cool}={D5,D6,D7,D9}

Examples:
3 positive
1 negative

Proportions of each class in this subset:
$p_+ = 0.75$
$p_- = 0.25$

$Entropy(S_{cool}) = -0.25\log_2 0.25 - 0.75\log_2 0.75 = \mathbf{0.811}$

Gain

Now we can compare the entropy of the system ***before*** we divided it into subsets using "Temperature", with the entropy of the system ***afterwards***. This will tell us how good "Temperature" is as an attribute.

The entropy of the system after we use attribute "Temperature" is:

$$(|S_{hot}|/|S|)*E(S_{hot}) + (|S_{mild}|/|S|)*E(S_{mild}) + (|S_{cool}|/|S|)*E(S_{cool})$$

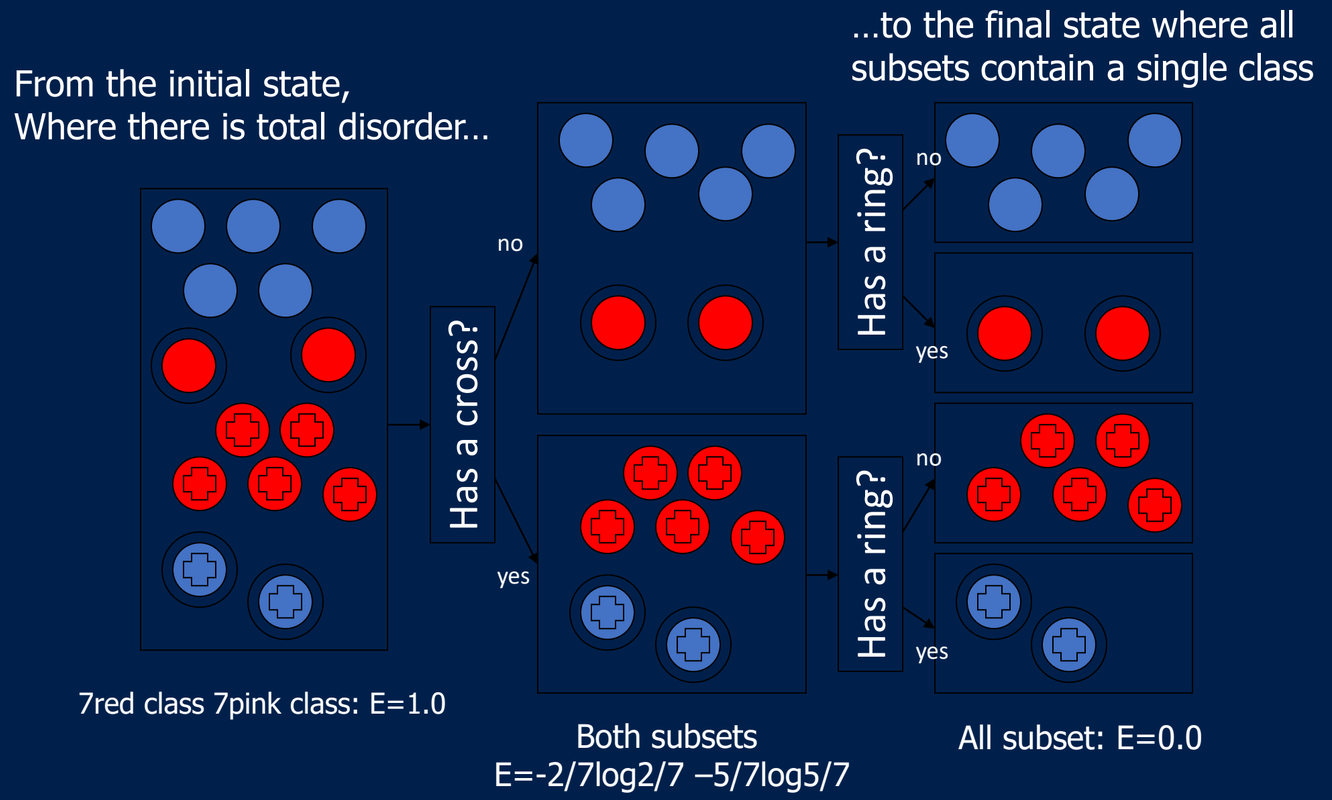
$$(4/14)*1.0 \quad + \quad (6/14)*0.918 \quad + \quad (4/14)*0.811 = \mathbf{0.9108}$$

This difference between the entropy of the system before and after the split into subsets is called the ***gain***:

$$Gain(S, A) = \overbrace{Entropy(S)}^{E(before)} - \overbrace{\sum_{v \in Values(A)} \frac{|S_v|}{|S|} Entropy(S_v)}^{E(afterwards)}$$

Gain(S,Temperature) = 0.940 - 0.9108 = **0.029**

Decreasing Entropy



Tabulating the Possibilities

Attribute=value	|+|	|-|	E	E after dividing by attribute A	Gain
Outlook=sunny	2	3	-2/5 log 2/5 – 3/5 log 3/5 = 0.9709	0.6935	0.2465
Outlook=o'cast	4	0	-4/4 log 4/4 – 0/4 log 0/4 = 0.0		
Outlook=rain	3	2	-3/5 log 3/5 – 2/5 log 2/5 = 0.9709		
Temp'=hot	2	2	-2/2 log 2/2 – 2/2 log 2/2 = 1.0	0.9108	0.0292
Temp'=mild	4	2	-4/6 log 4/6 – 2/6 log 2/6 = 0.9183		
Temp'=cool	3	1	-3/4 log 3/4 – 1/4 log 1/4 = 0.8112		
Etc…					

This shows the entropy calculations…

Table continued…

E for each subset of A	Weight by proportion of total	E after A is the sum of the weighted values	Gain = (E before dividing by A) – (E after A)
-2/5 log 2/5 – 3/5 log 3/5 = **0.9709**	0.9709 x 5/14 = **0.34675**	0.6935	0.2465
-4/4 log 4/4 – 0/4 log 0/4 = **0.0**	0.0 x 4/14 = **0.0**		
-3/5 log 3/5 – 2/5 log 2/5 = **0.9709**	0.9709 x 5/14 = **0.34675**		
-2/2 log 2/2 – 2/2 log 2/2 = **1.0**	1.0 x 4/14 = **0.2857**	0.9109	0.0292
-4/6 log 4/6 – 2/6 log 2/6 = **0.9183**	0.9183 x 6/14 = **0.3935**		
-3/4 log 3/4 – 1/4 log 1/4 = **0.8112**	0.8112 x 4/14 = **0.2317**		

…and this shows the gain calculations

Gain

- We calculate the gain for all the attributes.

- Then we see which of them will bring more ‘order’ to the set of examples.

- Gain(S,Outlook) = **0.246**
- Gain(S,Humidity) = 0.151
- Gain(S,Wind) = 0.048
- Gain(S, Temp’) = 0.029

- The first node in the tree should be the one with the highest value, i.e. ‘*Outlook*’.

ID3 (Decision Tree Algorithm: (Quinlan 1979))

- ID3 was the first proper decision tree algorithm to use this mechanism:

Building a decision tree with ID3 algorithm

1. *Select the attribute with the most gain*
2. *Create the subsets for each value of the attribute*
3. *For each subset*
    1. *if not all the elements of the subset belongs to same class repeat the steps 1-3 for the subset*

Main Hypothesis of ID3: The simplest tree that classifies training examples will work best on future examples (Occam's Razor)

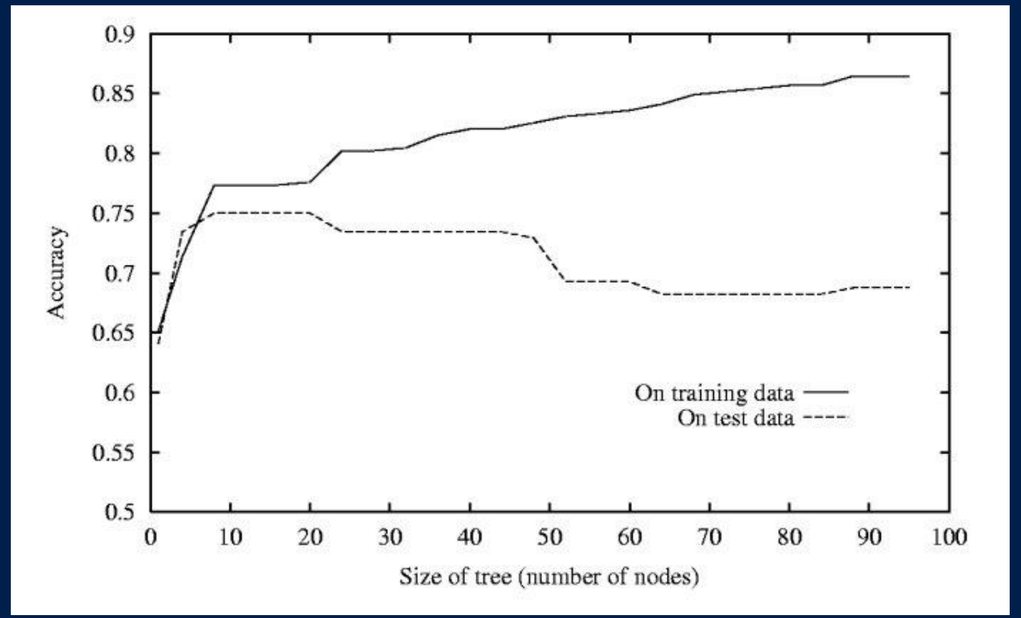
ID3 (Decision Tree Algorithm)

- Function DecisionTtreeLearner(*Examples, TargetClass, Attributes*)

- create a *Root node for the tree*
- **if** all *Examples are positive,* **return** the single-node tree *Root, with label = Yes*
- **if** all *Examples are negative,* **return** the single-node tree *Root, with label = No*
- **if** *Attributes list is empty,*
  - **return** the single-node tree *Root, with label = most common value of TargetClass in Examples*
- **else**
  - *A =* the attribute from *Attributes with the highest information gain with respect to Examples*
  - Make *A the decision attribute for Root*
  - **for** each possible value *v of A:*
    - add a new tree branch below *Root, corresponding to the test A = v*
    - let *Examplesv be the subset of Examples that have value v for attribute A*
    - **if** *Examplesv is empty* **then**
      - add a leaf node below this new branch with label = most common value of *TargetClass in Examples*
    - **else**
      - add the subtree DTL(*Examplesv, TargetClass, Attributes - { A })*
    - **end if**
- **end**
- **return** *Root*

The Problem of Overfitting

- Trees may grow to include ***irrelevant attributes***
- ***Noise*** may add ***spurious nodes*** to the tree.
- This can cause ***overfitting*** of the ***training data*** relative to ***test data.***



Hypothesis *H* **overfits** the data if there exists *H′* with greater error than *H*, over training examples, but less error than *H* over entire distribution of instances.

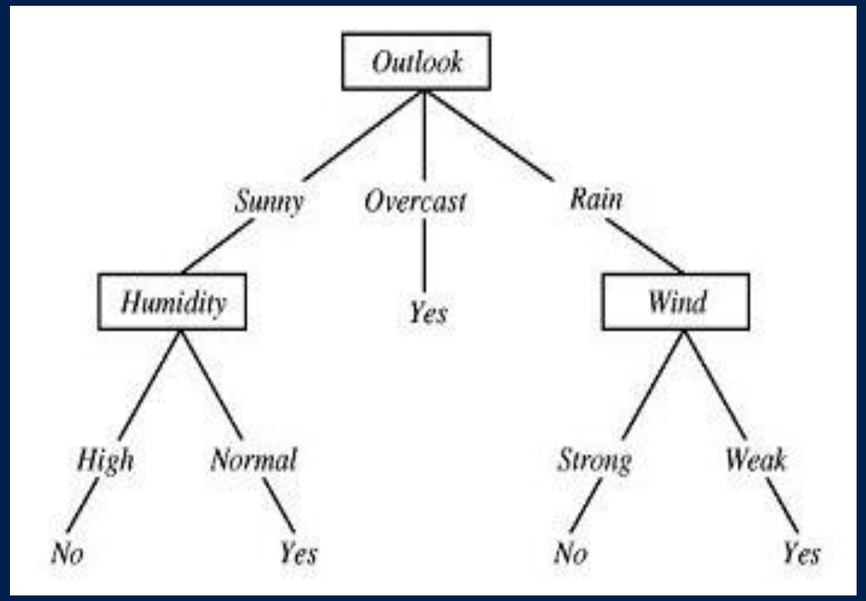
Fixing Over-fitting

Two approaches to pruning

Prepruning: Stop growing tree during the training when it is determined that there is not enough data to make reliable choices.

Postpruning: Grow whole tree but then remove the branches that do not contribute good overall performance.

Rule Post-Pruning



Rule post-pruning

- prune (generalize) each rule by removing any preconditions (*i.e., attribute tests) that result in improving its accuracy over the validation set*

- sort pruned rules by accuracy, and consider them in this order when classifying subsequent instances

- **IF (Outlook = Sunny) ^ (Humidity = High) THEN PlayTennis = No**

- Try removing **(Outlook = Sunny)** condition or **(Humidity = High)** condition from the rule and select whichever pruning step leads to the biggest improvement in accuracy on the validation set (or else neither if no improvement results).

- converting to rules improves readability

Advantage and Disadvantages of Decision Trees

- Advantages:
  - Easy to understand and map nicely to a production rules
  - Suitable for categorical as well as numerical inputs
  - No statistical assumptions about distribution of attributes
  - Generation and application to classify unknown outputs is very fast

- Disadvantages:
  - Output attributes must be categorical
  - Unstable: slight variations in the training data may result in different attribute selections and hence different trees
  - Numerical input attributes leads to complex trees as attribute splits are usually binary

Homework

Given the training data set, to identify whether a customer buys computer or not, Develop a Decision Tree using ID3 technique.

age	income	student	credit_rating	buys_computer
<=30	high	no	fair	no
<=30	high	no	excellent	no
31…40	high	no	fair	yes
>40	medium	no	fair	yes
>40	low	yes	fair	yes
>40	low	yes	excellent	no
31…40	low	yes	excellent	yes
<=30	medium	no	fair	no
<=30	low	yes	fair	yes
>40	medium	yes	fair	yes
<=30	medium	yes	excellent	yes
31…40	medium	no	excellent	yes
31…40	high	yes	fair	yes
>40	medium	no	excellent	no

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THANK YOU!!

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