## 1 Decision Tree Learning

## 1.1

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 \begin{array}{l} {\rm Value}({\rm Outlook}) = {\rm sunny, \, overcast, \, rain \, S} = [9+, 5-] \\ {\rm S \, sunny} \leftarrow [2+, 3-] \\ {\rm Sovercast} \leftarrow [4+, 0-] \\ {\rm Srain} \leftarrow [3+, 2-] \\ {\rm Entropy}(S) = -\frac{9}{14} \cdot \log_2(\frac{9}{14}) - \frac{5}{14} \cdot \log_2(\frac{5}{14}) = 0.9403 \\ {\rm Entropy}(Ssunny) = -\frac{2}{5} \cdot \log_2(\frac{2}{5}) - \frac{3}{5} \cdot \log_2(\frac{3}{5}) = 0.9709 \\ {\rm Entropy}(Sovercast) = -1 \cdot \log_2(1) - 0 \cdot \log_2(0) = 0 \\ {\rm Entropy}(Srain) = -\frac{3}{5} \cdot \log_2(\frac{3}{5}) - \frac{2}{5} \cdot \log_2(\frac{2}{5}) = 0.9709 \\ {\rm Gain}(S,Outlook) = Entropy(S) - \frac{5}{14} \cdot Entropy(Ssunny) - \frac{4}{14} \cdot Entropy(Sovercast) - \frac{5}{14} \cdot Entropy(Srain) = 0.2467 \\ \\ Value(Humidity) = high(>75), low(\leq 75) \\ S = [9+, 5-] \\ Shigh \leftarrow [5+, 4-] \\ Slow \leftarrow [4+, 1-] \\ Entropy(S) = -\frac{9}{14} \cdot \log_2(\frac{9}{14}) - \frac{5}{14} \cdot \log_2(\frac{5}{14}) = 0.9403 \\ Entropy(Shigh) = -\frac{5}{9} \cdot \log_2(\frac{9}{5}) - \frac{4}{9} \cdot \log_2(\frac{4}{9}) = 0.9911 \\ Entropy(Slow) = -\frac{4}{5} \cdot \log_2(\frac{4}{5}) - \frac{1}{5} \cdot \log_2(\frac{1}{5}) = 0.7219 \\ Gain(S, Humidity) = Entropy(S) - \frac{9}{14} \cdot Entropy(Shigh) - \frac{5}{14} \cdot Entropy(Slow) \\ = 0.04524 \\ \\ \end{array}
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## 1.2

SplitInfo = 
$$-(5/14) \cdot \log_2(\frac{5}{14}) - \frac{4}{14} \cdot \log_2(\frac{4}{14}) - \frac{5}{14} \cdot \log_2(\frac{5}{14}) = 1.5774$$
  
 $GainRatio(Outlook) = \frac{Gain(Outlook)}{SplitInfo} = 0.156$   
 $SplitInfo = -\frac{9}{12} \cdot \log_2(\frac{9}{14}) - \frac{5}{14} \cdot \log_2(\frac{5}{14}) = 0.9403$ 

$$\begin{split} SplitInfo &= -\frac{9}{14} \cdot \log_2(\frac{9}{14}) - \frac{5}{14} \cdot \log_2(\frac{5}{14}) = 0.9403 \\ GainRatio(Humidity) &= \frac{Gain(Humidity)}{Splitinfo} = 0.048 \end{split}$$

## 1.3

$$\begin{aligned} & \text{Value}(\text{Temp}) = \text{high}(\+i70), \ low(\le 70) \\ & S = [9+,5-] \\ & Shigh \leftarrow [5+,4-] \\ & Slow \leftarrow [4+,1-] \\ & Entropy(S) = -\frac{9}{14} \cdot \log_2(\frac{9}{14}) - \frac{5}{14} \cdot \log_2(\frac{5}{14}) = 0.9403 \\ & Entropy(S \ high) = -\frac{5}{9} \cdot \log_2(\frac{5}{9}) - \frac{4}{9} \cdot \log_2(\frac{4}{9}) = 0.9911 \\ & Entropy(S \ low) = -\frac{4}{5} \cdot \log_2(\frac{4}{5}) - \frac{1}{5} \cdot \log_2(\frac{1}{5}) = 0.7219 \\ & Gain(S, Temp) = Entropy(S) - \frac{9}{14} \cdot Entropy(Shigh) - \frac{5}{14} \cdot Entropy(Slow) \\ & = 0.04524 \end{aligned}$$

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\begin{split} Value(Windy) &= true, false \\ S &= [9+,5-] \\ Strue \leftarrow [3+,3-] \\ Sfalse \leftarrow [6+,2-] \\ Entropy(S) &= -\frac{9}{14} \cdot \log_2(\frac{9}{14}) - \frac{5}{14} \cdot \log_2(\frac{5}{14}) = 0.9403 \\ Entropy(Strue) &= -\frac{1}{2} \cdot \log_2(\frac{1}{2}) - \frac{1}{2} \cdot \log_2(\frac{1}{2}) = 1 \\ Entropy(Sfalse) &= -\frac{3}{4} \cdot \log_2(\frac{3}{4}) - \frac{1}{4} \cdot \log_2(\frac{1}{4}) = 0.6226 \\ Gain(S, Windy) &= Entropy(S) - \frac{6}{14} \cdot Entropy(Strue) - \frac{8}{14} \cdot Entropy(Sfalse) \\ &= 0.1559 \end{split}
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**Explanation:** Outlook is the attribute with the largest information gain, therefore, it is chosen as the decision node.

We can draw a decision tree by mapping through the root node to the leaf node one by one

