CIS 419/519: Homework 1

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Although the solutions are entirely my own, I consulted with the following people and sources while working on this homework: {http://www.cs.utep.edu/vladik/cs5315.13/cs5315_13kader.pdf}

1 Decision Tree Learning

a. Show your work:

$$InfoGain(PainLocation) = Info(X) - Info(X|PainLocation)$$

$$Info(X) = -\frac{9}{14}\log_2\frac{9}{14} - \frac{5}{14}\log_2\frac{5}{14} = 0.9402$$

$$InfoGain(PainLocation) = Info(X) - \frac{5}{14}(-\frac{3}{5}\log_2\frac{3}{5} - \frac{2}{5}\log_2\frac{2}{5}) - \frac{5}{14}(-\frac{2}{5}\log_2\frac{2}{5} - \frac{3}{5}\log_2\frac{3}{5}) - 0 = 0.2467$$

$$InfoGain(Temperature) = Info(X) - Info(X|Temperature)$$

$$= Info(X) - \frac{4}{14}(-\frac{2}{4}\log_2\frac{2}{4} - \frac{2}{4}\log_2\frac{2}{4}) - \frac{10}{14}(-\frac{7}{10}\log_2\frac{7}{10} - \frac{3}{10}\log_2\frac{3}{10}) = 0.02499$$

b. Show your work:

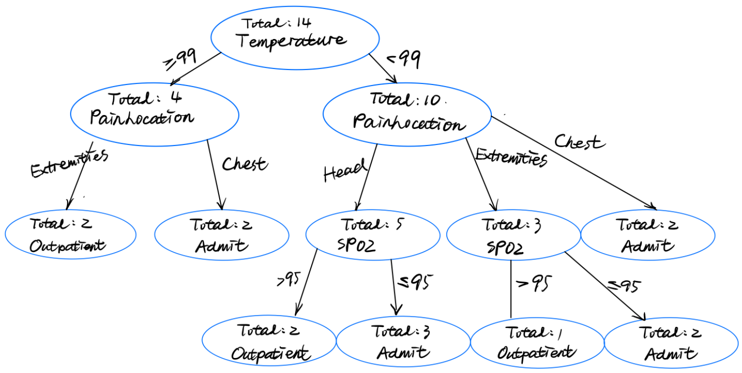
$$SplitInformation(PainLocation) = -\frac{5}{14}\log_2\frac{5}{14} - \frac{5}{14}\log_2\frac{5}{14} - \frac{4}{14}\log_2\frac{4}{14} = 1.5774$$

$$GainRatio(PainLocation) = \frac{InfoGain(PainLocation)}{SplitInformation(PainLocation)} = \frac{0.2467}{1.5774} = 0.156397$$

$$SplitInformation(Temperature) = -\frac{4}{14}\log_2\frac{4}{14} - \frac{10}{14}\log_2\frac{10}{14} = 0.86312$$

$$GainRatio(Temperature) = \frac{InfoGain(Temperature)}{SplitInformation(Temperature)} = \frac{0.02499}{0.86312} = 0.028953$$

c.



d. No because finding the global optimal decision tree is NP hard which has been proved in May, 1976. The advantage of ID3 is that it uses greedy approach which turns out to be really fast. ID3 will not produce the optimal decision tree, however, it gives good enough approximation. For more that 50% of the datasets, ID3 can give the optimal solution.

2 Decision Trees & Linear Discriminants [CIS 519 ONLY]

A decision tree can include oblique splits by taking linear combinations features when growing the decision tree. By doing it this way, our nodes would be classified using more than one feature, and this would result in oblique split in the decision tree which may not be parallel to the axes.

For example, suppose we were training the data using the classic decision tree algorithms(ID3/C4.5), we are picking a single feature with highest information gain ratio for each node. If we want to do an oblique split, we pick the linear combination with highest information gain ratio for each node instead. The way we linearly combine those features is that we weigh each feature based on the information they can provide, then we multiply the features' information gain by their weight and sum up to get the info gain of this combination. After this, we choose the best combination of this node.

3 Programming Exercises

Features: What features did you choose and how did you preprocess them?
Parameters: What parameters did you use to train your best decision tree
Performance Table:

Feature Set	Accuracy	Conf. Interval [519 ONLY]
DT 1	a	b
DT 2	a	b
DT 3	a	b

Conclusion: What can you conclude from your experience?