
1

Give decision trees to represent the following Boolean expressions

(a) $A \wedge \neg B$

(b) $A \vee (\neg B \wedge C)$

(c) $A \oplus B$

(d) $(A \vee B) \wedge (\neg C \wedge D)$

2

Consider the following set of training examples

Instance	Class	A_1	A_2
1	+	T	T
2	+	T	T
3	-	T	F
4	+	F	F
5	-	F	T
6	-	F	T

(a) What is the entropy of this collection of training examples with respect to the target function classification?

(b) What is the information gain of A_2 relative to these training examples?

3

Suppose we generate a training set from a decision tree and then apply decision-tree learning to that training set. Is it the case that the learning algorithm will eventually return the correct tree as the training-set size goes to infinity? Why or why not?

4

Suppose that an attribute splits the set of examples E into subsets E_k and that each subset has p_k positive examples and n_k negative examples. Show that the attribute has zero information gain if the ratio $\frac{p_k}{p_k+n_k}$ is the same for all k.

Extra credit: Show that the attribute has strictly positive information gain unless the ratio $\frac{p_k}{p_k+n_k}$ is the same for all k.

5

A *decision graph* is a generalization of a *decision tree* that allows nodes (i.e., attributes used for splits) to have multiple parents, rather than just a single parent. The resulting graph must still be acyclic. Now, consider the XOR function of three binary input attributes, which produces the value 1 if and only if an odd number of the three input attributes has value 1.

(a) Draw a minimal-sized *decision tree* for the three-input XOR function.

(b) Draw a minimal-sized *decision graph* for the three-input XOR function.