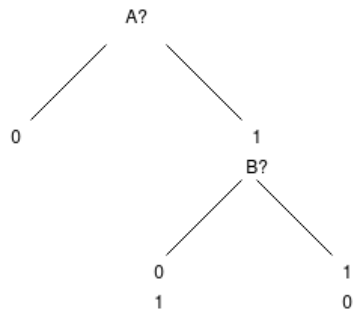
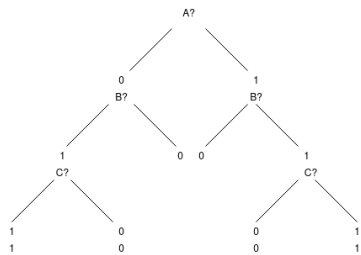
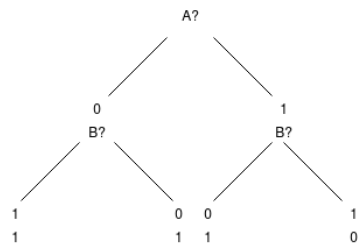
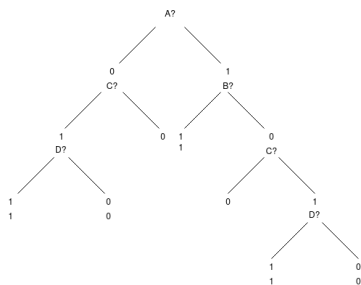


Problem 1

Give a decision tree to represent each of the following boolean functions:

Part a A and (not B)**Part b** A or (B and C)**Part c** A xor B**Part d** (A and B) or (C and D)

Problem 2

Consider this set of training examples:

| Instance | Classification | a1 | a2 |
|----------|----------------|----|----|
| 1 | + | T | T |
| 2 | + | T | T |
| 3 | - | T | F |
| 4 | + | F | F |
| 5 | - | F | T |
| 6 | - | F | T |

Thus, instances 1, 2, and 4 are positive; 3, 5, and 6 are negative;
a1 and a2 are the attributes

Part a What is the entropy of this set of training examples with respect to the target function classification?

The entropy of this set is 2 bits, since it takes 2 bits to determine the positive or negative value

Part b What is the information gain of a2 relative to these training examples?

The information gain of a2(as well as a1) is 1 bit, since knowledge of a2 reduces the entropy level of the classification by 1 bit.

Problem 3

This is a question about the Decision-Tree-Learning Algorithm (aka ID3)

Part a Show the decision tree that would be learned by ID3 assuming it is given the four training examples below for the EnjoySport? target concept.

| Example | Sky | AirTemp | Humidity | Wind | Water | Forecast | EnjoySport |
|---------|-------|---------|----------|--------|-------|----------|------------|
| 1 | Sunny | Warm | Normal | Strong | Warm | Same | Yes |
| 2 | Sunny | Warm | High | Strong | Warm | Same | Yes |
| 3 | Rainy | Cold | High | Strong | Warm | Change | No |
| 4 | Sunny | Warm | High | Strong | Cool | Change | Yes |

Positive and negative training examples for the target concept EnjoySport

Answer words

Part b Add the following training example, and compute the new decision tree. This time, show the value of the information gain for each candidate attribute at each step in growing the tree.

| Example | Sky | AirTemp | Humidity | Wind | Water | Forecast | EnjoySport |
|---------|-------|---------|----------|------|-------|----------|------------|
| 5 | Sunny | Warm | Normal | Weak | Warm | Same | No |

Answer words

Problem 4

Consider an ensemble learning algorithm that uses simple majority voting among K learned hypotheses. Suppose that each hypothesis has error ϵ and that the errors made by each hypothesis are independent of the others. Calculate a formula for the error of the ensemble algorithm in terms of K and ϵ , and evaluate it for the cases where $K=5, 10$, and 20 and $\epsilon=0.1, 0.2$, and 0.4 . If the independence assumption is removed, is it possible for the ensemble error to be worse than ϵ ?

Answer words

Problem 5

Find and sketch the following, and Report the actual polynomials found, simplifying to a single number each of their coefficients.

Part a 1st-order (linear) Lagrange interpolating polynomial through $(1,2)$ and $(3,5)$

Answer words

Part b 2nd-order (quadratic) Lagrange interpolating polynomial through $(-1,0.1)$, $(0,0)$, $(1,0.1)$

Answer words

Part c 1st-order (linear) least squares fit for points $(-1,0.1)$, $(0,0)$, $(1,0.1)$

Answer words

Problem 6

For this problem you will implement code to compute a "decision stump" for a real-life data set. The data is a massaged version (to make all variables 0-1 valued and remove instances with missing values) of the Congressional Voting Records in the UCI Machine Learning database. There is the classification (Attribute 1; 0=Democrat, 1=Republican) and 16 attributes (Attributes 2-17), which details votes on various bills taken from the 1984 United States Congressional Voting Records (0=no, 1=yes).

Part a Write a subroutine for Remainder(A), described on page 704 of R&N, that takes as its input value for A an integer between 2 and 17 corresponding to Attributes 2-17 as defined in the data file.

Answer words

Part b Write a subroutine for Gain(A), again described on page 704 of R&N, that again takes an integer input as above.

Answer words

Part c Write the necessary code to compute the decision stump. This entails (i) finding the attribute (2-17) that maximizes the information gain, (ii) counting how many of each classification appear in each branch, and (iii) computing the classifications you should use depending on that attribute's value. So, you are splitting on the yeses and nays (for each vote) and trying to predict the Dems and Reps. IDEA: how can you best predict the rep.s party by their vote on just one particular bill?

Answer words
