



12th Theoretical Assignment in Artificial Intelligence (WS 2006/2007)

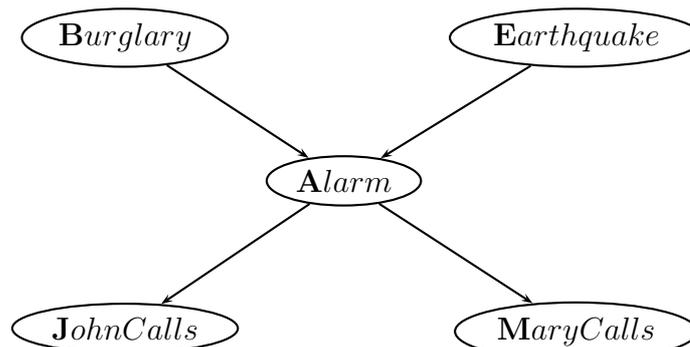
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Exercise 12.1 Consider the following set of training examples:

Instance	Classification	a_1	a_2
1	+	T	T
2	+	T	T
3	-	T	F
4	+	F	F
5	-	F	T
6	-	F	T

1. What is the entropy of this collection of training examples with respect to the target function classification?
2. What is the information gain of a_2 relative to these training examples?
3. What is the information gain of a_1 relative to these training examples?
4. Construct a decision tree with the decision-tree-learning algorithm from the lecture for the given set of training examples! Use information gain as the criterion for choosing the “best” attributes for splitting the tree!
5. Assume that *Instance 6* is an error with your measurement, and should in fact be classified as a + and not as a -. Does this change your decision tree? How?

Exercise 12.2 Consider the example from exercise 11.4 on the last exercise sheet.



The *a priori* probabilities and conditional probabilities are:

P(B)
.001

P(E)
.002

B	E	P(A)
T	T	.95
T	F	.94
F	T	.29
F	F	.001

A	P(J)
T	.90
F	.05

A	P(M)
T	.70
F	.01

In the lecture, we have seen the ENUMERATION-ASK algorithm (reproduced from Russell/Norvig: AIMA, 2003):

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function ENUMERATION-ASK( $X, e, bn$ ) returns a distribution over  $X$ 
  inputs:  $X$ , the query variable
          $e$ , observed values for variables  $E$ 
          $bn$ , a Bayesian network with variables  $\{X\} \cup E \cup Y$ 

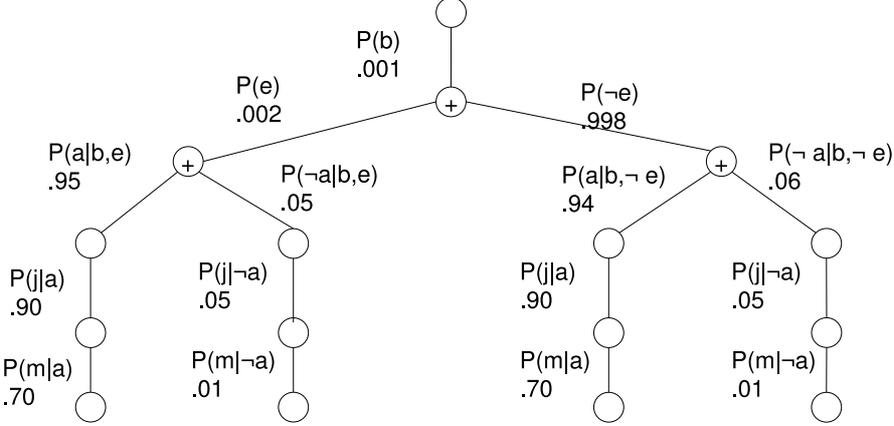
   $Q(X) \leftarrow$  a distribution over  $X$ , initially empty
  for each value  $x_i$  of  $X$  do
    extend  $e$  with value  $x_i$  for  $X$ 
     $Q(x_i) \leftarrow$  ENUMERATE-ALL(VARS[ $bn$ ],  $e$ )
  return NORMALIZE ( $Q(X)$ )

function ENUMERATE-ALL( $vars, e$ ) returns a real number
  if EMPTY?( $vars$ ) then return 1.0
   $Y \leftarrow$  FIRST( $vars$ )
  if  $Y$  has value  $y$  in  $e$ 
  then return  $P(y | Parents(Y)) \times$  ENUMERATE-ALL( $REST(vars), e$ )
  else return  $\sum_y P(y | Parents(Y)) \times$  ENUMERATE-ALL( $REST(vars), e_y$ )
  where  $e_y$  is  $e$  extended with  $Y = y$ 

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1. Consider the query $P(B|j, m)$. When calling ENUMERATION-ASK (where $X := B$, $e := \{j, m\}$, bn is the given network), ENUMERATE-ALL is called to compute $Q(b)$. This evaluation will produce a tree, which is reproduced below.

Use the ENUMERATE-ALL algorithm step by step to evaluate $ENUMERATE-ALL(\{B, E, A, J, M\}, \{j, m, b\})$ – i.e. follow the steps of the algorithm that produce the given tree!



2. Use ENUMERATION-ASK to answer the query $P(B|j, m)$! You can use the solution from part 1., and then do the missing parts.

One note about normalization: Remember that when you calculate the distribution of some variable, let's say D , where D can take the values d and $\neg d$, for example, then the probabilities of the possible values of D need to add up to 1. Furthermore, $P(d|e_1, \dots, e_n) + P(\neg d|e_1, \dots, e_n) = 1$. If the computation involves an unknown normalization constant α , such that $P(d|e_1, \dots, e_n) = \frac{x}{\alpha}$, and $P(\neg d|e_1, \dots, e_n) = \frac{y}{\alpha}$, α can be computed easily by knowing that $P(d|e_1, \dots, e_n) + P(\neg d|e_1, \dots, e_n) = 1$. This value α is what NORMALIZE is supposed to determine. The result of normalization is the computed probability distribution multiplied by α (look also at p. 476 and p. 505 in Russell/Norvig).