

**Advanced Artificial Intelligence**

CMP9132M | Assessment Item 1

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The following report will entail an appraisal and analysis of a range of artificial intelligence techniques and consideration for the application of effective decision-making, problem solving and learning for solving a given issue.

**Task 1.A**

The first task of this assignment involves the ‘rare disease and test problem’ scenario where the environment being considered situates a total of two variables, these variables are the following:

* d: the person has the disease.
* t: the test is positive.

-Introduce the problem at hand

A key issue faced with the proposed problem is the incapacity to calculate the probability of having the disease given the test was positive, otherwise abbreviated as , due to uncertain variables being present in the calculation. This was especially the case as only a total of three different variables are taken as input variables from the user, namely , and .

-Introduce key concepts used to solve the issue

-Refer to academic literature to back up claims

-Explain how solution operates

-Justify strengths and weaknesses of solution

**Task 1.B**

This next task involved a probability computation based on a Bayesian Network structure which describes the relationship between the variables involved in this particular system. This can be observed in the figure below:

**Task 2**

-Introduce the case problem

A Markov model can be considered as a stochastic, statistical model which can be utilised for modelling randomly changing systems. For example, the Markov Chain model models the system state with a random variable which is assumed to change as time passes, where it is assumed that the probability distribution for the system only adheres to a dependency on the probability distribution observed in the previous state. However, the system presented with this task merely provides the emission distribution, transition distribution and the initial starting state probability which is assumed to be equiprobable. This in turn presents the implication that while this system has observations related to the system state, the state sequence and some of the system state sequence is hidden, thus the Markov chain model can be argued to not be an appropriate methodology for this particular system. In contrast, a Hidden Markov Model operates similar to a Markov Chain model but for a system where the observations are partially observable and contain hidden states. The Hidden Markov Model operates under the belief that each state in the system has a probability distribution relative to the possible output values, and therefore the sequence of output values can be used to determine more information about the system state sequence.

To embody this concept into the design of the solution that was being developed, the system required more information about the emission probability distribution the user could desire at each new state within the sequence of states of the system being modelled. This operates under a recursive loop which constantly requests for new user input during each iterations, whereby the user is prompted to input an appropriate sequence of symbols from the vocabulary defined within the system, these being either: “Warm”, “Cold”, “Hot”, “Freezing”. The input received from the user will refer to a series of possible emission probability distributions that are known and pre-set in the system.

warm = [0.45,0.00 cold = [0.45,0.00

0.00,0.05] 0.00,0.05]

hot = [0.05,0.00 freezing = [0.05,0.00

0.00,0.45] 0.00,0.45]

The emission probability distributions describe the raw probabilities for each emission symbol being output. In contrast, the transition probability distributions describe the raw probabilities of what the next state could be given the values that reside in the current state. However, as previously discussed, this system features hidden states which describe the operational status of the heater, these being either “ON” or “OFF”. Imperatively, the Hidden Markov model can be used to estimate the values of the hidden states through time as per sequence specified by the user, based on the output probability distribution of the previous states.

The Hidden Markov model fundamentally operates under two assumptions in regards to the data involved with the model, the first assumption being the First-Order Markov Chain assumption. This being that the next step in the sequence of states depends on the current state only and none of the previous states. As a result, it can be assumed that the transition to the next state will only depend on the state the system is currently in.

Sensor Markov Assumption

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