

Lab 3 TDDC17

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1 Part 2

1.1 Task 5

- (a) $P(\text{Meltdown}) = 2.578\%$, $P(\text{Meltdown}|\text{IcyWeather}) = 3.472\%$
- (b) $P(\text{Meltdown}|\text{PumpFailure}, \text{WaterLeak}) = 20\%$
 $P(\text{Meltdown}|\text{PumpWarning}, \text{WaterLeakWarning}) = 14.535\%$
 $P_{diff} = 20 - 14.535 = 5.465\%$ The probability of having a meltdown increase if there is a warning.
- (c) Some of the parameters in the model are not quantifiable. For example the Icy-Weather variable is depending on temperature, humidity etc. It is hard to precisely measure the effect of a parameter separated from other parameters.
- (d) The temperature will be represented as a number or a range of temperature. This will increase the possible states in the domain and thus increase the complexity of the problem. The closer you get to a continuous temperature variable the number of possible states for the domain converge towards infinity.

1.2 Task 6

- (a) It represents the probability of all possible states for a node given the states of its parent nodes.
- (b) A joint probability distribution shows all combinations of distributions for all variables and their corresponding probability. Below we have shortened the names of the stochastic variables to their uppercase letters.

$$\begin{aligned}
 P(\text{"everything false"}) &= \\
 P(\neg M | \neg PFW, \neg PF, \neg WLW, \neg WL, \neg IW) &\times \\
 P(\neg PFW | \neg PF, \neg WLW, \neg WL, \neg IW) &\times \\
 P(\neg PF | \neg WLW, \neg WL, \neg IW) &\times \\
 P(\neg WLW | \neg WL, \neg IW) &\times \\
 P(\neg WL | \neg IW) &\times \\
 P(\neg IW) &\implies \\
 \implies P(M = f | PF = f, WL = f) &\times \\
 P(\neg PFW | \neg PF) &\times \\
 P(\neg WLW | \neg WL) &\times \\
 P(\neg WL | \neg IW) &\times \\
 P(\neg PF) &\times \\
 P(\neg IW) &= \\
 = 0.999 * 0.95 * 0.95 * 0.9 * 0.9 * 0.95 &= 0.6937792... \approx 69\% \text{ This is a common state.}
 \end{aligned}$$

- (c) $P(\text{Meltdown}|\text{PumpFailure} = t, \text{WaterLeak} = t) = 20\%$
 Since we know the state of all the parent nodes for the node of interest, no other nodes matter.

(d) The probability of Meltdown being true.

$$\begin{aligned}
 P(M|PF, \neg PFW, \neg WL, \neg WLW, \neg IW) &= \text{PF is unknown} = \\
 \alpha \sum P(M|\neg PFW, \neg WL, \neg WLW, \neg IW, PF = e) &= \\
 \alpha \sum^n P(M|PF = e, \neg WL) \times & \\
 P(\neg PFW|PF = e) \times & \\
 P(PF = e) \times & \\
 P(\neg WLW|\neg WL) \times & \\
 P(\neg WL|\neg IW) \times & \\
 P(\neg IW) = & \\
 = \alpha(0.001 * 0.95 * 0.9 * 0.95 * 0.9 * 0.95 + 0.15 * 0.1 * 0.1 * 0.95 * 0.9 * 0.95) = & \\
 \alpha(0.00069 + 0.00122) = 0.00191284875\alpha &
 \end{aligned}$$

In the same way the probability of meltdown being false is calculated.

$$P(\neg M|PF, \neg PFW, \neg WL, \neg WLW, \neg IW) = \dots = 0.70068340125\alpha$$

Now we calculate the scaling factor:

$$\alpha = \frac{1}{0.00191284875 + 0.70068340125} = 1.42329253821$$

This gives us the normalized probabilities:

$$P(M|PF, \neg PFW, \neg WL, \neg WLW, \neg IW) = 0.0027$$

$$P(\neg M|PF, \neg PFW, \neg WL, \neg WLW, \neg IW) = 0.9973$$

2 Part 3

- (a) When no observations are made $P(\text{Survives}) = 0.99001$ and when we observe that the radio is not working $P(\text{Survives}|\neg \text{radio}) = 0.98116$. We see that the probability of survival decrease when the radio is not working.
- (b) The probability of survival increase with 0.5% when the bicycle is added.
 $P(\text{Survives}) = 0.99505$
- (c) In a Bayesian Network the complexity increase with factor $\mathcal{O}(n2^n)$, for n variables. Although it is possible to model any function in propositional logic with Bayesian Networks it is very performance limited for large networks.
 An alternative to exact inference would be to use approximations, for example the way Monte Carlo Simulations each time use different random values for the probability functions.

3 Part 4

For our extended model see `task4b.xml`.

- (a) With our implementation of Mr H.S the probability of survival increase to $P(Survives) = 0.99583$. Instead of hiring Mr H.S we could switch to a pump with probability of failure $P(PumpFailure) = 0.06$ or better to get a better probability of survival. With this pump we would insted get $P(Survives) = 0.99615$.
- (b) We could solve this by adding a new node representing $P(WLW \vee PFW)$. In our network we also assume that Mr H.S is awake and not on the toilet since it matches the problem given. The probability of survival is now: $P(Survives) = 0.98551$.
- (c) Humans are much more random in their behaviour which makes it almost impossible to predict their behaviour. Also to model a humans behaviour we would need many more, if not infinite number of variables. We also don't have a model for the gain of experience that would most likely change the probabilities over time for Mr H.S.
- (d) For example you could use Markov chains which instead of generating samples from scratch generate them with dependence of the preceeding sample.