Lab 3

Task for part II

5.

- a. P(meltdown | no observations made) = 0.02578, P(meltdown | Icy weather) = 0.03472
- b. P(meltdown | pumpfailurewarning ∧ waterleakwarning) = 0.14535, P(meltdown | pumpfailure ∧ waterleak) = 0.2
 - The difference is that there is a possibility that there has been no failure when the warnings have been activated. Thus the risk for meltdown is lower as there might have been no failure.
- c. You need a lot of observations to get accurate numbers, and in the case of nuclear meltdowns you might not have a lot. Meltdown is also dependent on a lot of other factors hence why we think it's the hardest to estimate.
- d. Different temperature alternatives: too low, ok, too high.
 P(waterleak | temperature too low) = about the same as icy weather
 P(waterleak | temperature ok) = lower than icy weather
 P(waterleak | temperature too high) = unknown, but there might be a heightened risk

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a. It represents the probability of this variable being true/false based on what states previous variables, affecting this one, are (true/false).

b.

- Joint probability distribution is a probability distribution which describes the probability of two or more random variables falling in a specified range for those variables.
- ii. P(IW, WL, WLW, PF, PFW, MD) = P(IW) * P(WL | IW) * P(WLW | IW, WL) * P(PF | IW, WL, WLW) * P(PFW | IW, WL, WLW, PF) * P(MD | IW, WL, WLW, PF, PFW) = 0.95 * 0.9 * 0.95 * 0.9 * 0.95 * 0.999 = 0.694
- iii. Yes, it seems fairly common.

C.

- i. P(MD | PF, WL) = 0.2
- ii. No, us knowing any other variables' states would not matter in this case since we know both are true. If we did not know their states, but the WaterLeakWarning would have been true, then the probability for Waterleak to be true would be higher, and thus the probability for meltdown to be true would also be higher. But in this case it is irrelevant since we know both of the variables', which are directly affecting the meltdown probabilities, states.

d.

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W=known variables observed values
       P(MD | PFW = fulse, WL = false, WLW = false, IW = false)
 = & . P(MD, KV) = E
 = a · E P(MD, KV, PF)
= X . E P(MDI PFW, WL, WLW, IW, PF) . P(PFW/WL, WLW, IW, PF)
                                   . P(NL | WLW, IW, PF) . P(WLW IW, PF) . P(IW) PF)
= x. (0.001 · 0.95 · 0.9 · 0.95 · 0.95 · 0.9 + 0.15 · 0.9 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 · 0.95 
 0.999 . 0.95 . 0.9 . 0.95 . 0. 95 . 0.9 + 0.85 . 0.9 . 0.9 . 0.95 . 0.95 . 0.9
                               (PF: fulse)
= a (0.001913, 0.700683) &
         a. 0.001913+ a.0, 700633= a (0.001713+0 700683)=1
        a=1,42329
      P(MD= true | KV) = 0.001913 = 000272
      P(MD= talse (KV) = X . 0. 700687 = 0.99728
         Answer: Probability of meltilown = 0,00272
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Task for part III

- 1. Look at xml-file
- 2.
- a. Assuming we do not know any other variables' states and by stereo we are referencing the radio, his chances of survival went from 0.99 to 0.98.
- b.

- i. Without bicycle variable and not knowing any states, the owner's chances of survival are 0.99026.
- ii. With bicycle variable and not knowing any states, the owner's chances of survival are 0.99516

C.

- i. The complexity of exact inference in bayesian network is a #P-hard problem. The number of nodes in the problem model increases the computation time more than linearly to calculate the probability with respect to all the variables and both the known and unknown states.
- ii. An alternative is to try to do a approximation, instead of having to check all the variables of a bayesian model you could possibly just check with the depending neighbours of a variable's state you want to calculate thus reducing the complexity of the calculation. This would give a less exact answer but would probably be a lot faster to calculate.

Task for part IV

- 1. Look at xml-file
- 2. -
- a. It would partly compensate for the lack of H.S.'s expertise. If the pump is better (more reliable) then the probability for failure in that regard would lower, but the probability for waterleak failure would stay the same.

b.

- i. HS's chance of survival 0.98295.
- ii. The disjunction is regarding whether there is a WaterleakWarning, Pumpfailure warning or both. This can be solved by introducing a new variable *CoworkerHearsWarningsignals*, which is dependent on both of the earlier warnings, and thus cover the disjunction. If CoworkerHearsWarningsignals is true (which it is in this case) then we know that one or both of the warningsignals has gone of with different probabilities.
- c. You assume that a person is affected by only a few and often too limited amount of factors which also should have different probabilities at different times (HS could be hungover one day and thus the probability for a bad performance would be higher). The real world is more complex and also dynamic.
- d. We could model this by having different states with different probabilities for transitions between these. For example if we are at the state IcyWeather there is a probability 0.8 that we are at this state the next day too, and there is a probability of 0.2 that we move on to the state NotIcyWeather the next day. And at NotIcyWeather there is a 0.9 probability that we stay on this state the next day, and a 0.1 probability that we move to IcyWeather the next day.