TDDC17 Artificial Intelligence :

Lab 3 : Bayesian Network

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Part 2 : Inference in an existing Bayesian network

This third lab session explores the concept of Bayesian Networks.

Questions

a) What is the risk of melt-down in the power plant during a day if no observations have been made ? What if there is icy weather ?

If no observation has been made, the risk of melt-down in the power plant is equal to **0.02578**. If there is icy weather it rises to **0.03472**.

b) Suppose that both warning sensors indicate failure. What is the risk of a meltdown in that case ? Compare this result with the risk of a melt-down when there is an actual pump failure and water leak. What is the difference ? The answers must be expressed as conditional probabilities of the observed variables, $P(Meltdown|...)$***.***

$P(Meltdown|PumpFailureWar \bigcap WaterLeakWar) = 0.14535$

$P(Meltdown|PumpFailure \bigcap WaterLeak) = 0.2$

The probability of having a meltdown whent there is a pump failure and a water leak is higher.

c) The conditional probabilities for the stochastic variables are often estimated by repeated experiments or observations. Why is it sometimes very difficult to get accurate numbers for these ? What conditional probabilities in the model of the plant do you think are difficult or impossible to estimate ?

It is challenging to measure precisely the effect of each parameter taken separately from the others on a given event. Furthermore some parameters are simply not quantifiable, for example *IcyWeather*. Is this relative to the temperature ? The humidity rate ? The pressure ? In this problem we have no proper definition, therefore it is impossible to estimate.

d) Assume that the "IcyWeather" variable is changed to a more accurate "Temperature" variable instead (don't change your model). What are the different alternatives for the domain of this variable ? What will happen with the probability distribution of P(WaterLeak / Temperature) in each alternative ?

The domain will have more possible states. Instead of having simply IcyWeather true or false based on unknown parameters, the temperature will be represented as a number (e.g. 3°C) or as a range of temperature (e.g. 5-10°C).

a) What does a probability table in a Bayesian network represent ?

The probability table shows the probability of each possible state of a node given the states of the parent nodes.

b) What is a joint probability distribution ? Using the chain rule on the structure of the Bayesian network to rewrite the joint distribution as a product of P(child/parent) expressions, calculate manually the particular entry in the joint distribution of P(Meltdown=F, PumpFailureWarning=F, PumpFailure=F, WaterLeakWaring=F, WaterLeak=F, IcyWeather=F). Is this a common state for the nuclear plant to be in ?

The chain rule provide us with the following equation

$P(everythingfalse) = P(IW) * P(PF) * P(PW|PF) * P(MD|PF, WL) * P(WL|IW) * P(WLW|WL)$

$$= 0,95 * 0,9 * 0,95 * 1 * 0,9 * 0,95 = 0,69$$

Yes this is a common state for the nuclear plant.

c) What is the probability of a meltdown if you know that there is both a water leak and a pump failure ? Would knowing the state of any other variable matter ? Explain your reasoning !

$P(Meltdown|PumpFailure \bigcap WaterLeak) = 0,8$

No other variables matter. When all the parents values are observed they alone determine the child value.

d) Calculate manually the probability of a meltdown when you happen to know that PumpFailureWarning=F, WaterLeak=F, WaterLeakWarning=F and IcyWeather=F but you are not really sure about a pump failure. Hint : Use the Exact Inference formula near the end of the slides, or in sec. 14.4.1 in the book. This formula includes both conditioning on the variables you know (evidence) and marginalizing (summing) over the variable(s) you do not know (often called unobserved or hidden). You need to calculate this both for P(Meltdown=T/...) and P(Meltdown=F/..) and normalize them so that they sum to 1. This normalization factor is the alpha symbol in the equation. With this formula you could answer any query in the network, though it will be impractical for cases with many unobserved variables. A suggestion is to move the terms that do not involve the pump failure variable out of the sum over the two states pump failure can be in (T/F). You may use inference in the applet for verification purposes, but small differences is expected due to rounding errors.

The chain rule provide us with the following equation

$P(MD = T|PFunsure, everythingelsefalse)$

$= P(IW) * P(WL|IW) * P(WLW|WL) * [P(PF = T) * P(PW|PF = T) * P(MD = T|PF = T, WL) + P(PF = F) * P(PW|PF = F) * P(MD = T|PF = F, WL)]$

$= 0,95 * 0,9 * 0,95 * (0,1 * 0,1 * 0,16 + 0,9 * 0,95 * 0,01) = 0,008$ (1)

$P(MD = F|PFunsure, everythingelsefalse)$

$= P(IW) * P(WL|IW) * P(WLW|WL) * [P(PF = T) * P(PW|PF = T) * P(MD =$

$F|PF = T, WL) + P(PF = F) * P(PW|PF = F) * P(MD = F|PF = F, WL)]$

$= 0,95 * 0,9 * 0,95 * (0,1 * 0,1 * 0,84 + 0,9 * 0,95 * 0,99) = 0,694$ (2)

$(1) and (2) => \alpha = 1/(0,008 + 0,69) = 1,42$

$(1) 0,008 * 1,42 = 0,012$

$(2) 0,694 * 1,42 = 0,988$

Part 3 : Extending a network

During the lunch break, the owner tries to show off for his employees by demonstrating the many features of his car stereo. To everyone's disappointment, it doesn't work. How did the owner's chances of surviving the day change after this observation ?

With the assumption that the radio does not work, the probability of survival is $P(Survives) = 0.98116$ which is less than the probability of survival without making any observation on the radio, $P(Survives) = 0.99001$.

The owner buys a new bicycle that he brings to work every day. The bicycle has the following properties : P(bicycle_works) = 0.9 $P(survives|moves \bigcap melt-down \bigcap bicycle\_works) = 0.6$ $P(survives|moves \bigcap melt-down \bigcap bicycle\_works) = 0.9$ ***How does the bicycle change the owner's chances of survival ?***

With the addition of the bicycle to the network, the probability of survival increases slightly $P(Survives) = 0.99505$.

It is possible to model any function in propositional logic with Bayesian Networks. What does this fact say about the complexity of exact inference in Bayesian Networks ? What alternatives are there to exact inference ?

Part 4 : More extensions

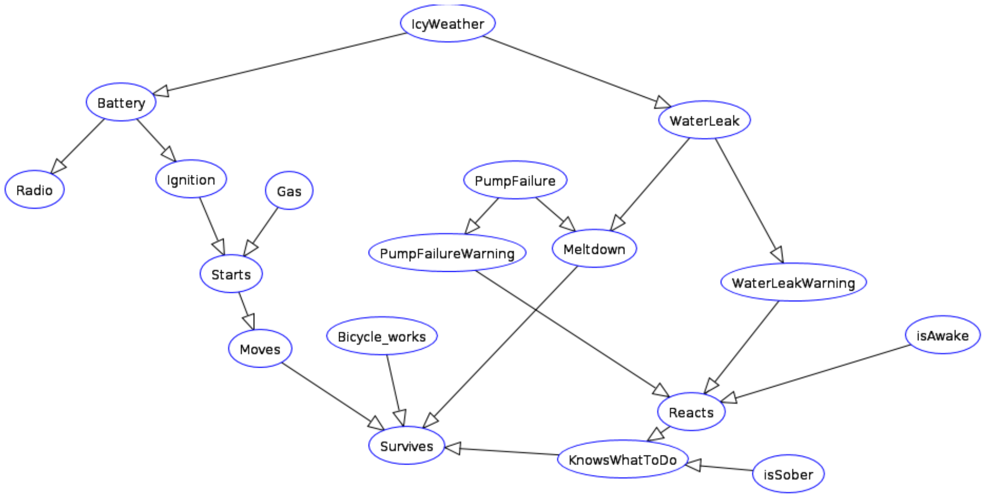

FIGURE 1 – Adding Mr H.S.

With the addition of Mr H.S. to the network, the probability of survival increases slightly $P(Survives) = 0.99522$.

With the observation of Meltdown and Reacts, $P(Survives) = 0.82104$.

The owner had an idea that instead of employing a safety person, to replace the pump with a better one. Is it possible, in your model, to compensate for the lack of Mr H.S.'s expertise with a better pump ?

Without Mr H.S. it is possible to achieve the same probability of survival by decreasing the probability of PumpFailure by only 1

Mr H.S. fell asleep on one of the plant's couches. When he wakes up he hears someone scream : "There is one or more warning signals beeping in your control room !". Mr H.S. realizes that he does not have time to fix the error before it is to late (we can assume that he wasn't in the control room at all). What is the chance of survival for Mr H.S. if he has a car with the same properties as the owner ? Hint : This question involves a disjunction (A or B) which can not be answered by querying the network as is. How could you answer such questions ? Maybe something could be added or modified in the network.

What unrealistic assumptions do you make when creating a Bayesian Network model of a person ?

We make the assumption that human actions are predictable. Furthermore, we do not consider the gain of experience which would modify the probabilities, for exemple Mr H.S. will be less incompetent.

Describe how you would model a more dynamic world where for example the "IcyWeather" is more likely to be true the next day if it was true the day before. You only have to consider a limited sequence of days.

We would have to add nodes representing the weather of the previous days. The node representing the previous day should have more impact on IcyWeather that the day before and so on until the last weather saved.