TDT4171 Artificial Intelligence Methods
Exercise 3

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When choosing a decision problem tried to find a situation which happened frequently in our daily lives, which we could relate to and were we can easily judge the results. Additionally we wanted to select a problem which could contain small differences between different candidates in how they view the world, in our paper this is the two authors different interpretations of how important sleep, weather, physical shape and so on is when deciding to attend a lecture or not.

Taken these arguments into account we also wanted a problem which contained both uncertainty and probability factors and at least ten of them. After some thought the decision was made and the problem we chose reads as follows: *Should I go to lecture Friday morning at 8AM?*

Model

Having chosen our problem and utility function, we had to find our dependencies and influencing properties, some are mentioned already above. Directly influencing our decision is the following:

1. How many days are left to the exam?
2. Precipitation
3. Degrees outside
4. Our control of the subject at hand
5. Are we hungover? Or more generally: are we feeling OK?

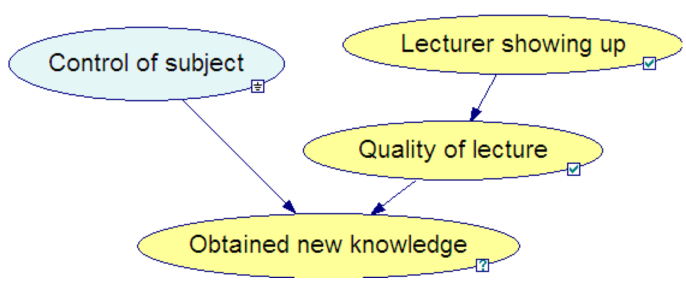
Our physical shape is influenced by how many beers drunk last night and how many hours of sleep one has obtained since then.

Then we have some uncertainties which could only be observed by actually going to the lecture:

1. Does the lecturer show up?
2. How was the quality of the lecture?
3. By attending, did you obtain new knowledge?
4. Did any friends show up at the lecture?

Here we tried to pinpoint our beliefs of the real world – how often to we attend a really good lecture? Given that the lecturer shows up and the lecture is good, do we obtain new knowledge? How often do the lecturer not show up? Etc.

In order to measure/quantify the results we need a utility function - which should depict a value of some property in our life. It felt natural to chose this function to measure our life quality depending on which decision we make and how we are feeling. In our model this utility function is called 'Quality of life'. Let us touch upon some intresting features in our model and describe some of the thought process behind our values and how these may be different by another oberserver. If we slice our model and focus on one part of a time, a prominent and highly influencing sub-tree is shown below.



Note that whether we obtain new knowledge or not is highly dependent on the decision node controlling if we actually go to the lecture or not. By not going the probability of obtaining new knowledge is zero. Hence we need a dependency from 'Go to lecture' to 'Obtained new knowledge', not shown in Figure 1.

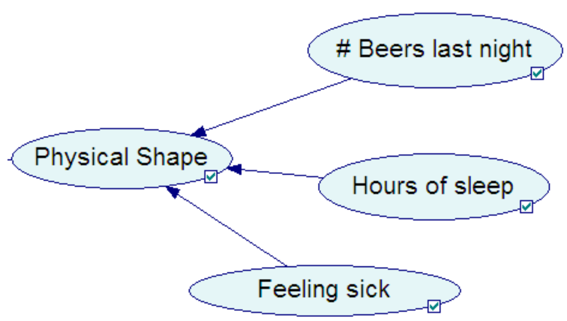
The probability of the lecturer not showing up is 4%, a value found by analyzing lectures so far in various courses and our experience with soon three years at the Norwegian University of Technology and Science. Given that the lecturer shows up, the probability of a good lecture is 20%, a average lecture is 60% and a bad lecture is 20%. These numbers are based on the same grounds as above.

If the lecturer does not show up - the probability of a bad lecture is of course 100%.

Perhaps the most interesting node properties in this sub-system, which we are focusing on here, is the probabilities defining when we obtain new knowledge. We both agreed that the highest potential for learning is when we have average control of the subject and the quality of the lecture is high.

Go to lecture	Yes		
Control of subject	Some		
Quality of lecture	Low	Medium	High
None	0.3	0.1	0.05
Some	0.5	0.45	0.3
Lots	0.2	0.45	0.65

Let us draw our focus now on another important section of our model, namely our physical shape, which of course plays a large role when deciding whether to stay home or not.



As one can see there are three factors which affect our physical shape, namely the amount of beers consumed the night before, the amount of sleep and our general feeling (are we feeling sick?). Notably if you are feeling sick our physical form is generally characterized as bad, the only exception being when you've slept a reasonably amount of time. An interesting discussion took place regarding probabilities of sleep and amount of beer. In general the numbers are highly independent and hence important to change if you want the system to depict your own life situation. An example is shown; Martin and Herman has the following probabilities regarding alcohol:

	Martin	Herman
Number of beers	Probability	
0	0.35	0.55
1-2	0.2	0.1
1-2	0.2	0.1
3-4	0.1	0.05
5-6	0.15	0.2
7+	0.2	0.1

Which yields the following results (when no evidence is set):

	Martin	Herman
Go to lecture?	Less than a month to exam	
Yes	22.99	23.99
No	7.17	6.04

Considering the fact that ten other probabilities are affecting our utility function, a difference of 1 between Herman and Martin due to a small change in alcohol habits is a strong verification on how important the independent variables are in our model (and for life in general). They should both generally go to the lectures, but since Herman is drinking less – he is more likely to show up. We could experiment with different values for both 'feeling sick' and 'amount of sleep', but we'll keep the discussion short and let that be an exercise for the reader.

Finally, the weather is an important factor for both us and our friends. Hence those nodes are affecting our utility function as well as the uncertain variable 'friends showing up'. Notice too that a friend may be feeling sick (just as we may be), but this variable can not be the same as the one connected to 'Physical Shape', even though they contain the same probabilities. If it were connected to both nodes it would translate to 'the probability for our friend being sick at the same time as we are feeling sick' – which, of course, is not what we want.

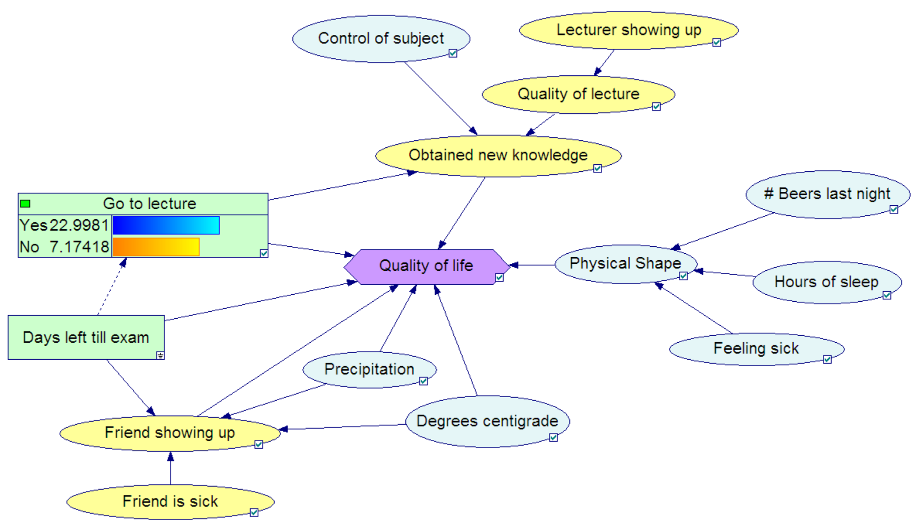
For both the precipitation and degrees we used a 50% chance for precipitation/no-precipitation and below 0 degrees/above 0 degrees, respectively. This way the model works in a general season and these two nodes need to be tuned with respect to city and season. For example you would have a high probability for precipitation in the autumn (especially in Trondheim) compared to the summer.

A brief discussion of the utility function is appropriate. As mentioned in the introduction our decision problem is based on a lot of properties, all except one is discussed above. The remaining factor is the actual decision of going to the lecture or not. Why? The answer is simply shown with an example. Assume that we are feeling really bad, it is cold outside and raining. Now the utility function has to depict a higher value for staying home (in order to feel better), rather than attending the lecture – and hence the actual attendance affect our result.

An interesting property was found when entering probabilities for the different definitions. By placing ‘Go to lecture’ on the top we observed that the utility function, or rather the values, was inversed depending on weather we attended the lecture or not. That is given the same properties we obtained the inverse utility value. This is illustrated well with a random example:

Go to lecture?	*Yes*	*No*
Obtained new knowledge	No	No
Physical shape	Bad	Bad
Friend showing up	No	No
Days left to exam	More than two months	More than two months
Degrees centigrade	Below 0	Below 0
Precipitation	No	No
Value	-55	55

Our finished model ended up looking like the figure below. Please consult the GeNiE file for details regarding the model:



In this figure we’ve cleared all evidence and set the number of days till exam to be ’Less than a month’.

Problems encountered

We encountered numerous problems when doing this exercise, many of which might be rooted in our relative inexperience in dealing with bayesian networks. At first we gave every variable way too many possible states, e.g. degrees centigrade had five different states. This resulted in enormous amounts of different states to consider in the utility-function, and we had to simplify to just above and below zero degrees centigrade. This made it actually possible to consider the different states in the utility function, but made our model much simpler, perhaps even too simple to be a good tool in a real world situation. We found that balancing these concerns was very complicated, especially since adding just a single extra state to a variable directly considered in the utility function increased the state-space enormously.

Even with the "simplified" state-space we ended up with, the amount of states meant populating the utility function was a rather large data entry job. This lead to us not being able to really ponder every possibility as much as we would like, possibly skewing the results to some degree.

In general we found GeNIe to be somewhat frustrating to work with. For one, it was Windows only – forcing us to use IDI's terminal server which added some headaches, and we would have much prefered to have implemented this ourselves in a programming language or framework of our choosing.

Dicussion of results

That we chose to be two students co-operating on this exercise posed a few concerns. For example, the amount of sleep each of us needs to feel good the next day is not nearly comparable, and one of us in general drinks more than the other. As shown earlier, we tried with different values for the variables where we behave differently, yielding at times significantly differing results. In the end, we had to compromise and chose values that we felt represented the pair of us in the most accurate manner.

Generally the model behaved as we wanted it to, even with the discrepancies discussed. If we set evidence to seven or more beers, less than four hours sleep etcetera, we end up with a reccomendation of not going to the lecture. If however we've slept well, hold back on drinking and the weather is fair, the model reccomends attending as expected.