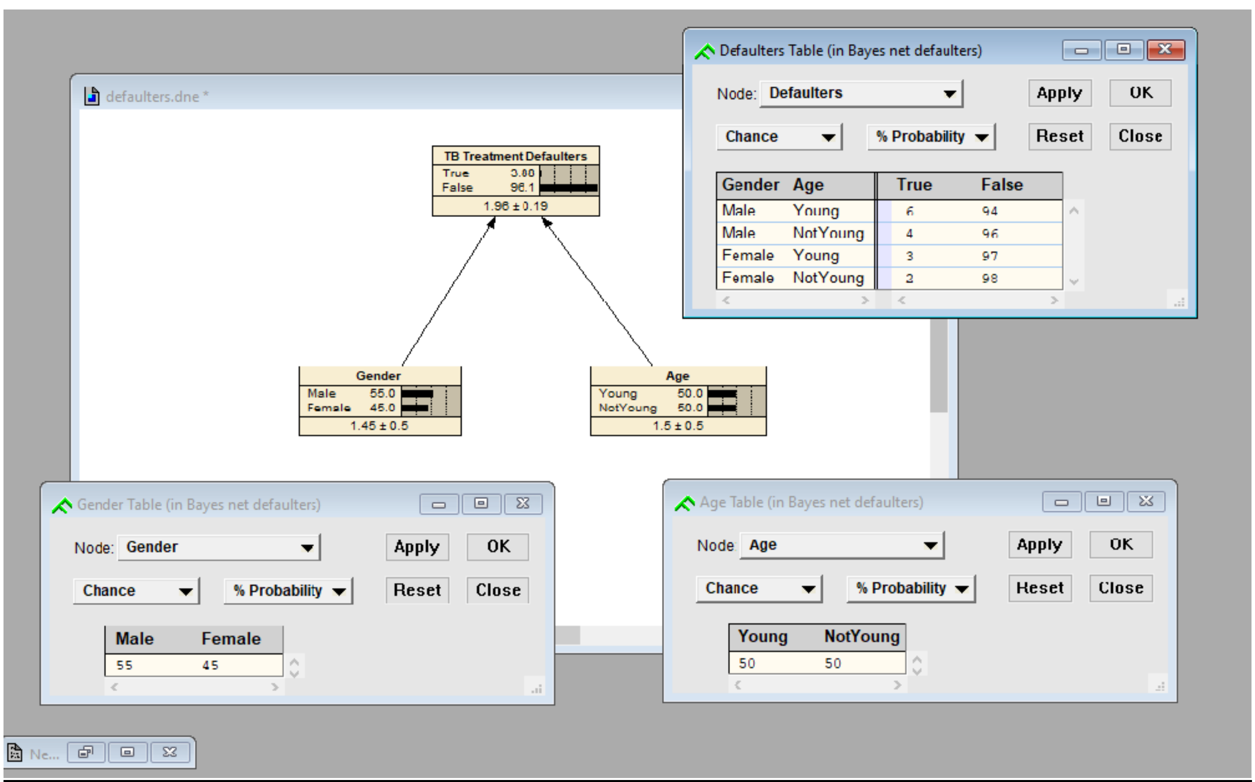
AI Final Exam 2019

Question 1

H ~ has heart disease
P ~ tested positive
Pr(H) = 0.02
Pr(-H) = 0.98
Pr(P|H) = 0.85
Pr(-P|H) = 0.15
Pr(-P|-H) = 0.9
Pr(P|-H) = 0.1

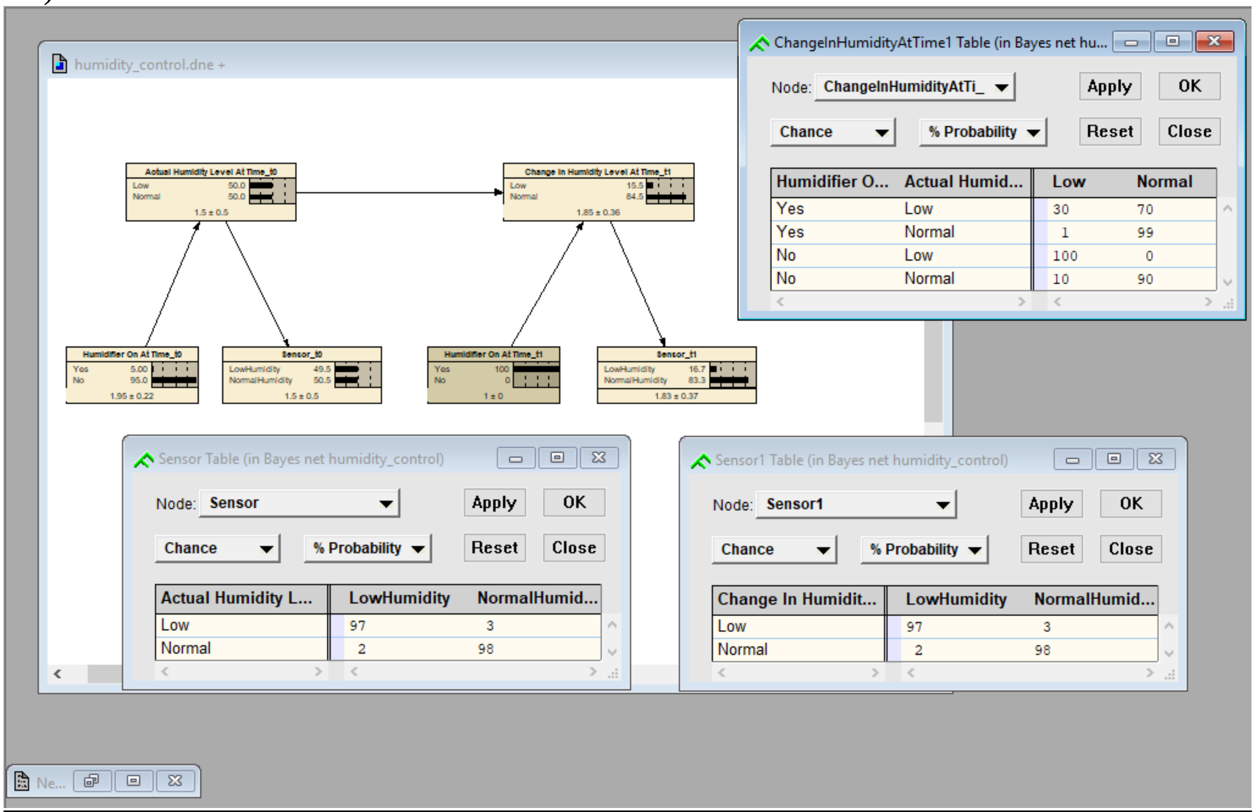
Pr(H|P) = (Pr(P|H).Pr(H))/(Pr(P|H))(Pr(H))+(Pr(P|-H))(Pr(-H))
= (0.85)(0.02)/((0.85)(0.02)+(0.1)(0.98))
= 0.017/(0.017+0.098)
= 0.017/0.115
= <u>0.148</u>

Question 2



Question 3

3.1)



3.2) Please find attached, prob_proj.py

3.3) 10-20 minutes

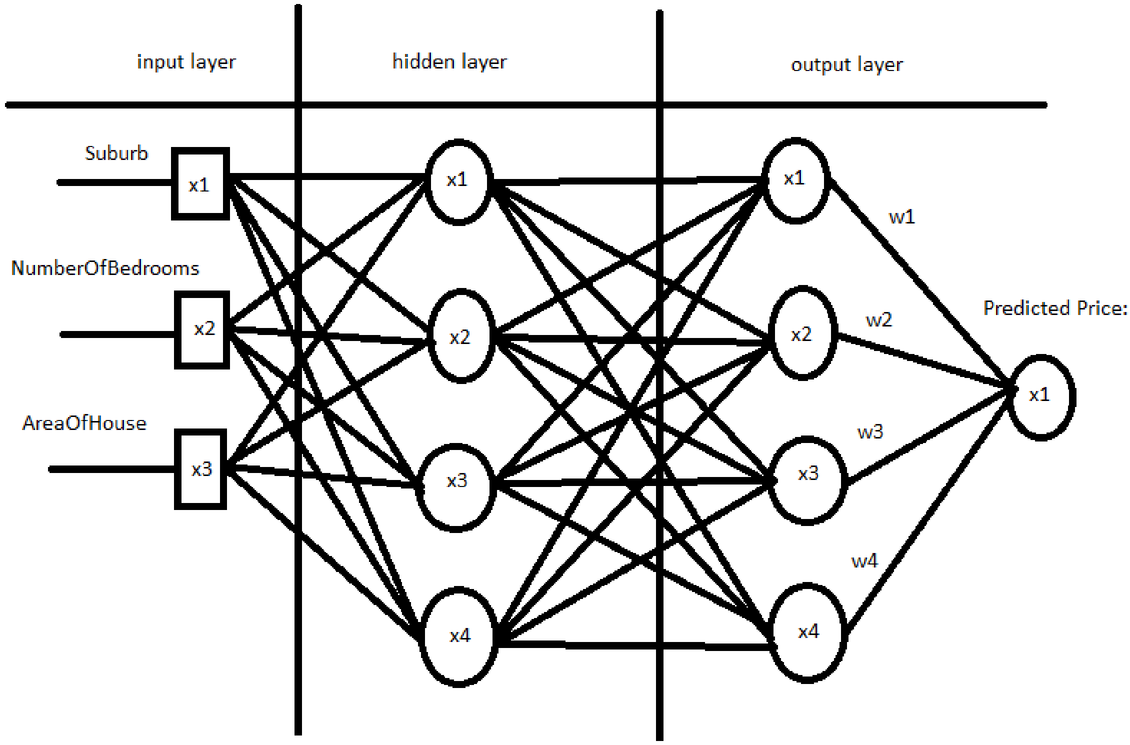
3.4) Adding an arc to a Dynamic Bayesian Network that crosses two time steps has the effect of basing the next set of probabilities (at t=n+2) on the current set of probabilities (at t = n) among other possible contributing factors. Adding this arc would contradict the Markov property/ assumption that the state of the world at time (t) is only dependent on the previous state (t-1) and all information at previous states (t-2, t-3 ...) is incorporated in the state at (t-1). The arcs between timestamps must be exactly the same.

Question 4

4.1) Algorithm:
Split the data into 10 equal subsets.
total_error=0
for i=1 to 10
    Hold out partition 10 as the test set
    Train on the remaining examples
    error_k = Test on partition 10

total_error += error_k
average_error = total_error/10

4.2)



Note: Please assume that every node (xi) has a corresponding weighting (wi) such as those demostrated in the output layer; where i is the unique identifier of each node.

4.3) There are four dimensions of the weight space for the problem above. These four dimensions describe the fact that there are four weighted nodes for each corresponding output node.

4.4) For a given function, we know that the minimum (or maximum) is given by the coordinates at which the gradient is equal to zero. Gradient descent tells you how to change the weights of a given input node such that the cost function is minimized. These changes in weighting increase the predictive accuracy of the neural network. Instead of selecting multiple output nodes with varying degrees of confidence, the network will adjust such that it begins to select fewer optimal output nodes (hypothesis) with a high degree of confidence.

4.5) The resultant model is NOT the best that can be found. It is possible to find another set of weight values for the same data partitions that may produce a better model than the resultant model. We know this because algorithms such as gradient descent simply aim to minimize the cost by adjusting weights such that the closest minimum cost is found. This closest (local) minimum cost may not necessarily be the lowest (global) cost in the entire cost function.

Question 5

Round 0:

3	0	0	0	-3
2	0	0	0	-3
1	0	0	0	0
States	**1**	**2**	**3**	**4**

- Assumed V0=0 for all states

Round 1:

3	0	0	-0.405	-3
2	0	0	1.89	-3
1	0	0	0	1.89
States	**1**	**2**	**3**	**4**

- S33 = 0.9[0.15*-3] = 0.9[-0.45] = -0.405
- S23 = 0.9[0.7*3] = 0.9[2.1] = 1.89
- S14 = 0.9[0.7*3] = 0.9[2.1] = 1.89

Round 2:

3	0	-0.055	0.786	-3
2	0	0	1.835	-3
1	0	0	1.446	2.145
States	**1**	**2**	**3**	**4**

- S33 = 0.9[(0.7*1.89)+(0.15*-3)] = 0.9[1.323-0.45] = 0.9[0.873] = 0.756
- S23 = 0.9[(0.7*3)+(0.15*-0.405)] = 0.9[2.1-0.06075] = 0.9[2.03925] = 1.835
- S14 = 0.9[(0.7*3)+(0.15*1.89)] = 0.9[2.3838] = 2.145
- S32 = 0.9[0.15*-0.405] = 0.9[-0.06075] = -0.055
- S13 = 0.9[(0.7*1.89)+(0.15*1.89)] = 0.9[1.323+0.2835] = 0.9[1.6065] = 1.446

Question 6

In Q-learning, the epsilon value refers to the propensity of the agent to explore its environment. Initially, it is important to set a high epsilon value so that the agent can explore the environment to find new ways to maximize its reward. As the agent finds new ways of maximizing reward, the epsilon (tendency to explore) should converge towards zero. This convergence indicates the agent's ability to exploit the environment such that it tends to select the best course of action from memory (given that the environment hasn't changed over time). There is a tradeoff between exploration and exploitation due to the fact that as much as an agent could find a valid solution, it should still explore its environment to make sure that this valid solution is in fact the optimal. Therefore, set a high epsilon value if you want an agent to explore its environment; and a low epsilon value if you want the agent to greedily exploit known methods of maximizing reward.

Question 7

Environment/AI technique	**Fully vs partially observable**	**Episodic vs sequential**	**Discrete vs. continuous**	**Deterministic vs. stochastic**	**Static vs. dynamic**	**Known vs unknown**
Bayesian Decision networks	Only useful to an agent given a fully observable environment as the environment will be used to inform the probabilities and conditional probabilities	Ideal for episodic environments due to the fact that an agent of requires the current set of states and their associated probabilities	Discrete environments are ideal. The agent must know exactly how it can act given a set of predefined possibilities	An agent can only cope with deterministic environments. The network must be defined probabilistically in the event of any uncertainty	An agent can only cope with a static environment. The environment cannot be allowed to change while deliberation occurs	Agents can only cope with known environments as the outcomes of all decisions possible are known and do not change the environment
Dynamic Decision Networks	Only useful to an agent given a fully observable environment as the environment will be used to inform the probabilities and conditional probabilities over	Ideal for a sequential environments due to the fact that an agent of requires knowledge of previous states and current states. If this entire set of information is currently available, episodic	Discrete environments are ideal. The agent must know exactly how it can act given a set of predefined possibilities	An agent can only cope with deterministic environments. The network must be defined probabilistically in the event of any uncertainty	An agent can only cope with a static environment. The environment cannot be allowed to change while deliberation occurs	Agents can only cope with known environments as the outcomes of all decisions possible are known and do not change the environment

	time	environments suffice.				
Reinforcement Learning	An agent is better suited for a partially observable environment due to its ability to choose whether to explore or exploit given its Q function	Sequential environments are preferred as the agent may want to exploit known solutions to increase its reward	Discrete environments are ideal. The agent must know exactly how it can act given a set of predefined possibilities	Stochastic environments are preferable as they allow for exploration of the given environment. There is a high degree of uncertainty	An agent can only cope with a static environment. The environment cannot be allowed to change while deliberation occurs	Unknown environments are preferred as they allow an agent to explore a set of actions which may alter its environment
Machine learning including Neural network	Partially observable environments work best as it is ideal to have the agent learn and correct itself given new information	Sequential environments are ideal as they allow for a machine learning agent to learn from past data	Discrete environments are ideal. The agent must know exactly how it can act given a set of predefined possibilities	Stochastic environments are preferable as they allow for exploration of the given environment. There is a high degree of uncertainty	An agent can only cope with a static environment. The environment cannot be allowed to change while deliberation occurs	Unknown environments are preferred as they allow an agent to deduce a plausible solution to the problem from training and test the solution in an unknown environment
Logic	Since logic is a top down approach, fully observable	Episodic environments are preferable as they allow the	Discrete environments are best suited to an agent as it requires a	Deterministic environments are ideal as the logic of an agent	Static environments are ideal but the agent is likely to	Agents are best suited for known environments as this knowledge

	environments are preferable as this information is used to inform a plan ahead	agent to gather knowledge on the environment to act logically	limited number of distinct clearly defined actions and percepts on which to base its logic	is unlikely to be able to adjust in order to deal with uncertainty nor randomness	cope with dynamic environments as well depending on the problem at hand	is used to inform the agents' knowledge