CS 3600 Project 3 Wrapper

CS3600 - Fall 2023

Due November 8th 2023 at 11:59pm EST via Gradescope

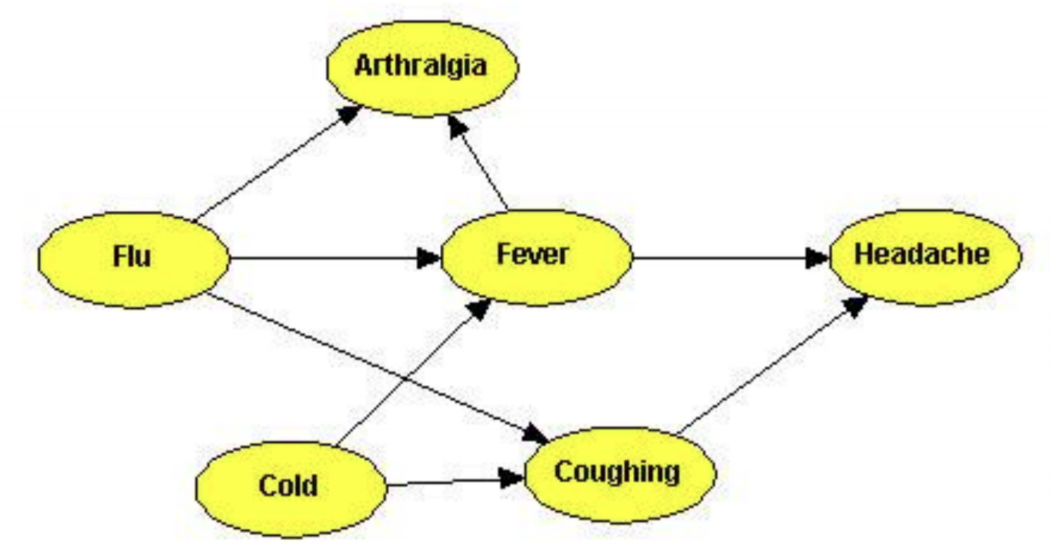


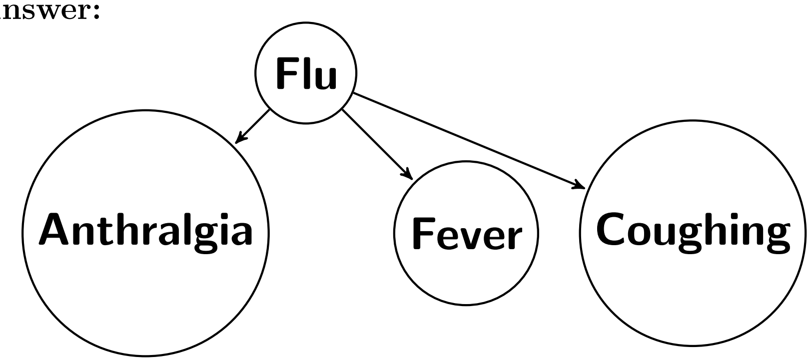
Figure 1: Example Bayesian network for medical diagnosis.
Source: http://song.bayesian.net/index.php/Bayesian_net

Probabilistic inference over Bayesian networks is a standard AI technique for medical diagnosis. Bayesian networks represent complex causal relationships between patient information, medical conditions, and symptoms. Probabilistic inference allows us to compute diagnostic queries, determining the likelihood of medical conditions given observed symptoms as evidence.Use the example Bayes net above as a prompt for the following questions.

Question 1

Recall that the naïve Bayes assumption is that no effects of a cause are also causes of each other. If two effects are correlated it is because they are related to the same, underlying cause. The naïve Bayes model provides an alternative representation for diagnostic inference. Draw a Bayes net representing the naïve Bayes model for diagnosing *Flu* given its symptoms (assume the symptoms of *Flu* are every successor of *Flu* in the Bayes net in Figure 1). Which model (the Bayes net in Figure 1 or the naïve Bayes model that you've constructed) is a richer representation? That is to say, is there anything we can represent with one model that we cannot represent with the other model?

Answer:



The naïve Bayes model is a simpler and more restrictive representation because it assumes independence between symptoms. This simplification is useful when you have limited data or want to make the modeling and inference process more tractable. However, the representation in Figure 1 allows for more realistic modeling of the dependencies among symptoms and their relationships to different conditions. It captures the fact that symptoms like Fever and Coughing can be shared by both Flu and Cold and that there can be dependencies among the symptoms themselves. Thus, the model in Figure 1 is a richer representation because it allows us to capture dependencies among symptoms and the fact that some symptoms can be caused by multiple conditions.

Question 2

$SICK_{t-1}$	$P(SICK_t = T \| SICK_{t-1})$	$P(SICK_t = F \| SICK_{t-1})$
T	0.7	0.3
F	0.5	0.5

Table 1: Transition Probabilities

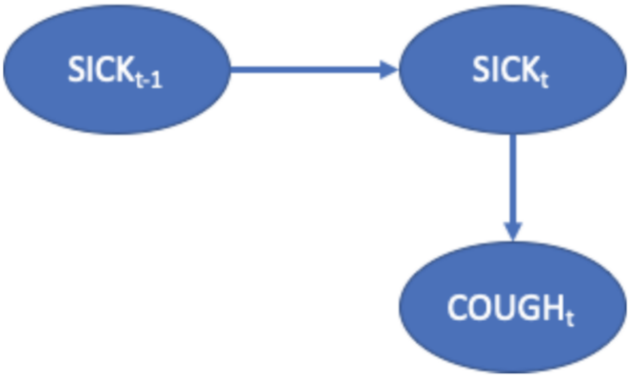
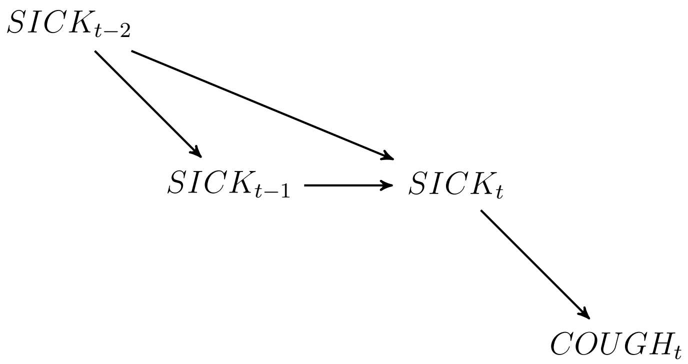


Figure 2: First Order Markov Dynamic Bayes Net

The traditional Dynamic Bayes Net has an unobservable random variable X_t that has a single parent of the value of X_{t-1}, which is the value of X at the previous time step. For example, SICK$_t$ is conditioned on SICK$_{t-1}$. This can capture a relationship such as "when one is sick, the probability is high that one is still sick at the next time step, and when one is not sick, one can become sick or stay well with equal probability". See the image for an example. However, if one were to use this Bayes network to predict the future, the model may conclude that people become sick randomly and then stay sick. This setup does not account for second-order effects, such as: "after one is sick for a while, the probability is high that one stops being sick". A 2-Markov assumption states that an unobservable random variable X_t is conditioned on X_{t-1} and X_{t-2}. **Using a time step equal to a week, draw a 2-Markov Dynamic Bayes Network that captures the intuition that one can become sick at any time**. When one is sick one is likely to remain sick unless they have been sick for two weeks, at which time they are likely to cease being sick. When one is sick, the probability of cough is high and when one is not sick, the probability of cough is low. **Show all the conditional probability tables; make up reasonable numbers to express the relationships described above.**



Answer:

Table 2: Conditional Probability Tables for the 2-Markov Dynamic Bayes Network

$SICK_{t-2}$	$SICK_{t-1}$	$P(SICK_t = T \mid SICK_{t-1}, SICK_{t-2})$	$P(SICK_t = F \mid SICK_{t-1}, SICK_{t-2})$
T	T	0.1	0.9
T	F	0.2	0.8
F	T	0.8	0.2
F	F	0.6	0.4

$SICK_t$	$P(COUGH_t = T \mid SICK_t)$
T	0.9
F	0.2

Question 3

Medical diagnosis with Bayesian networks are currently used as a *decision support systems* by healthcare professionals. An expert can input patient information and observed symptoms, and the decision support system outputs a set of possible diagnoses with associated likelihoods, but the final diagnosis decision is up to the medical professional. Why should we require a human supervisor to accept or override the decision of the AI diagnosis system? Name two (2) potential sources of error or unaccounted for situations for these Bayes net diagnosis models that are mitigated by having a trained healthcare professional make the final diagnosis decision.

Answer: A human supervisor is crucial in AI diagnosis systems for several reasons. First, Bayesian network models may not consider rare or novel medical conditions, and human experts can provide context and expertise in such cases. Second, these systems rely on accurate patient data, and errors or omissions can occur during data entry. A healthcare professional can ensure data accuracy and account for patient history, which the model may not fully capture. Additionally, the emotional and ethical aspects of delivering diagnoses and treatment options require human judgment and empathy. Therefore, human supervision ensures the most contextual and ethical medical decision-making, which an accuracy-driven AI system cannot provide.

Question 4

Publicly accessible online services often use databases and symptom matching to inform users of possible medical conditions given a list of symptoms. These services do not provide diagnosis likelihoods. Could providing a free online service with Bayes-net-based medical diagnosis have negative impacts on human behavior? Could they have positive impacts? If you answered yes to either question, give one example. If you answered no, explain why not.

Answer: Yes, providing a Bayes-net-based medical diagnosis service could have negative impacts if users rely solely on the automated results (not fully contextual) without seeking professional medical advice, leading to potential misinterpretation or unnecessary anxiety. However, it could have positive impacts by increasing health awareness and encouraging users to seek timely medical help, especially for potentially serious conditions that patients might have not thought of or overlooked.