✖

Sampling Methods

7/7 得分 (100%)

测验通过！

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1.

Forward Sampling. One strategy for obtaining an estimate to the conditional probability $P(\mathbf{y} \mid \mathbf{e})$ is by using forward sampling to estimate $P(\mathbf{y}, \mathbf{e})$ and $P(\mathbf{e})$ separately and then computing the ratio. We can use the Hoeffding Bound to obtain a bound on both the numerator and the denominator. Assume M is large. When does the resulting bound provide meaningful guarantees? Think about the difference between the true value and our estimate. Recall that we need $M \geq \frac{ln(2/\delta)}{2\epsilon^2}$ to get an additive error bound ϵ that holds with probability $1 - \delta$ for our estimate.

- [x] It provides a meaningful guarantee, but only when ϵ is small relative to $P(\mathbf{e})$ and $P(\mathbf{y}, \mathbf{e})$

正确

True. When ϵ isn't small with respect to $P(\mathbf{y}, \mathbf{e})$ and $P(\mathbf{e})$ the value of the estimated ratio $P(\mathbf{y}, \mathbf{e})$ /$P(\mathbf{e})$ can be far from the true value of $P(\mathbf{y}|\mathbf{e})$ even if the absolute value of ϵ and hence the absolute error in estimating $P(\mathbf{e})$ and $P(\mathbf{y}, \mathbf{e})$ is small.

- [ ] It provides a meaningful guarantee, but only when δ

is small relative to $P(\mathbf{e})$ and $P(\mathbf{y}, \mathbf{e})$

- ○ It never provides a meaningful guarantee.
- ○ It always provides meaningful guarantees.

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2.

Rejecting Samples. Consider the process of rejection sampling to generate samples from the posterior distribution $P(X \mid e)$. If we want to obtain M samples, what is the expected number of samples that would need to be drawn from $P(X)$?

- ○ $M \cdot P(X \mid e)$
- ○ $M \cdot (1 - P(e))$
- ○ $M/(1 - P(e))$
- ○ $M \cdot (1 - P(X \mid e))$
- ○ $M \cdot P(e)$
- ◉ $M/P(e)$

正确

This is correct because it accounts for the samples we will reject if they don't agree with the evidence and end up with keeping M samples. Let A be the total number of samples. Then probability of keeping each sample is $P(e)$. Therefore, $M = P(e) * A$.

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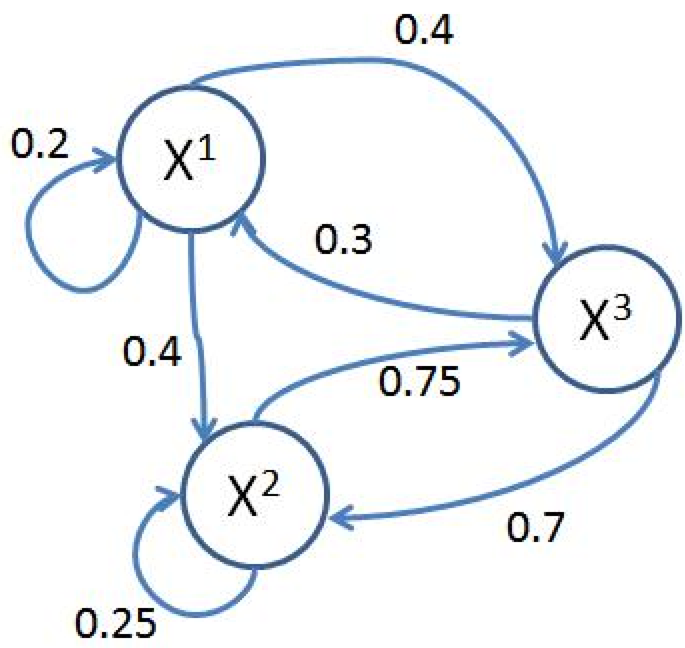
3.

Stationary Distributions. Consider the simple Markov chain shown in the figure below. By definition, a stationary distribution π for this chain must satisfy which of the following properties? You may select 1 or more options.



- [x] $\pi(x_1) = 0.2\pi(x_1) + 0.3\pi(x_3)$

正确

- [ ] $\pi(x_3) = 0.4\pi(x_1) + 0.5\pi(x_2)$

未选择的是正确的

- [ ] $\pi(x_1) = 0.2\pi(x_1) + 0.4\pi(x_2) + 0.4\pi(x_3)$

未选择的是正确的

- [ ] $\pi(x_1) = \pi(x_2) = \pi(x_3)$

未选择的是正确的

- [ ]

$$\pi(x_3) = 0.3\pi(x_1) + 0.7\pi(x_3)$$

未选择的是正确的

$$\pi(x_1) + \pi(x_2) + \pi(x_3) = 1$$

正确

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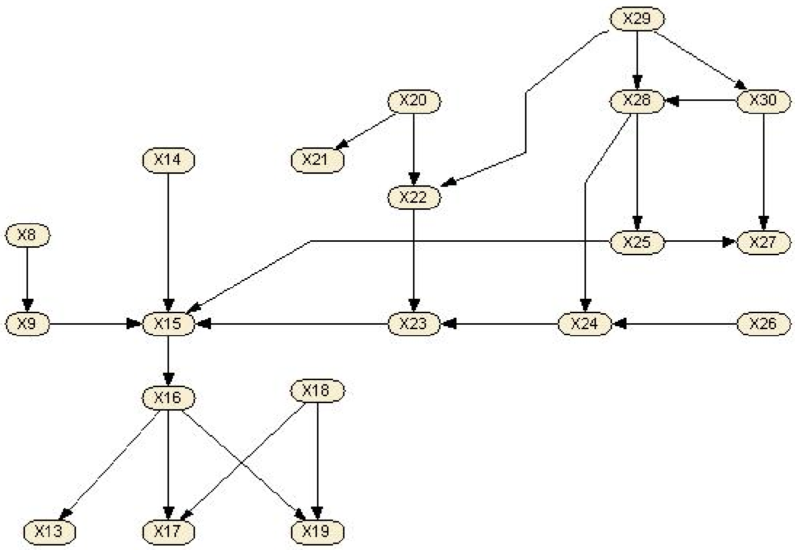
4.

***Gibbs Sampling in a Bayesian Network.** Suppose we have the Bayesian network shown in the image below.

If we are sampling the variable X_{23} as a substep of Gibbs sampling, what is the closed form equation for the distribution we should use over the value x'_{23} ? By closed form, we mean that all computation such as summations are tractable and that we have access to all terms without requiring extra computation.



None of these; they are all either incorrect or not in closed form

$P(x'_{23} \mid x_{22}, x_{24})P(x_{15} \mid x'_{23}, x_{14}, x_9, x_{25})$

- $\frac{P(x'_{23}|x_{22},x_{24})P(x_{15}|x'_{23},x_{14},x_9,x_{25})}{\sum_{x''_9,x''_{14},x''_{22},x''_{24},x''_{25}} P(x'_{23}|x''_{22},x''_{24})P(x''_{15}|x'_{23},x''_{14},x''_9,x''_{25})}$

- $P(x'_{23} \mid x_{-23})$ where x_{-23} is all variables except x_{23}

- $P(x'_{23} \mid x_{22}, x_{24})$

- $\frac{P(x'_{23}|x_{22},x_{24})P(x_{15}|x'_{23},x_{14},x_9,x_{25})}{\sum_{x''_{23}} P(x''_{23}|x_{22},x_{24})P(x_{15}|x''_{23},x_{14},x_9,x_{25})}$

正确

This is correct. This distribution can be computed based only on the Markov blanket of x_{23} .

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5.

Gibbs Sampling. Suppose we are running the Gibbs sampling algorithm on the Bayesian network $X \rightarrow Y \rightarrow Z$. If the current sample is $\langle x_0, y_0, z_0 \rangle$ and we sample y as the first substep of the Gibbs sampling process, with what probability will the next sample be $\langle x_0, y_1, z_0 \rangle$ in the first substep?

- $P(y_1 \mid x_0, z_0)$

正确

For Gibbs Sampling, we select one variable and keep others constant to compute the conditional probability of that variable being sampled given all the other variables.

- $P(x_0, y_1, z_0)$
- $P(y_1|x_0)$
- $P(x_0, z_0 \mid y_1)$

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6.

Collecting Samples. Assume we have a Markov chain that we have run for a sufficient burn-in time, and now wish to collect samples and use them to estimate the probability that $X_i = 1$. Can we collect and use every sample from the Markov chain after the burn-in?

- ○ Yes, and if we collect m consecutive samples, we can use the Hoeffding bound to provide (high-probability) bounds on the error in our estimated probability.
- ○ No, once we collect one sample, we have to continue running the chain in order to "re-mix" it before we get another sample.
- ◉ Yes, that would give a correct estimate of the probability. However, we cannot apply the Hoeffding bound to estimate the error in our estimate.

正确

This is correct because after the burn-in time the collected samples are all samples from the stationary (posterior) distribution. The Hoeffding bound cannot be used, because consecutive samples from the chain are not independent.

- ○ No, Markov chains are only good for one sample; we have to restart the chain (and burn-in) before we can collect another sample.

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7.

Markov Chain Mixing. Which of the following classes of chains would you expect to have the shortest mixing time in general?

- ○ Markov chains for networks with nearly deterministic potentials.

Markov chains where state spaces are well connected and transitions between states have high probabilities.

正确

This is correct because if you are able to move around the state space, you are more likely to mix in quickly.

Markov chains with many distinct and peaked probability modes.

Markov chains with distinct regions in the state space that are connected by low probability transitions.