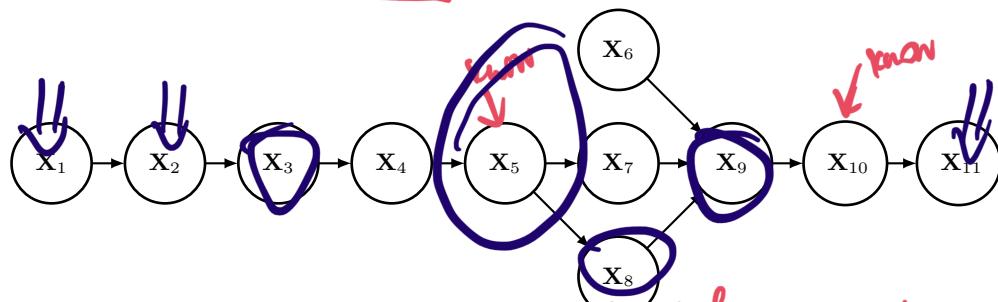


50.007 Machine Learning, Fall 2021
 Homework 5

Due Thursday 9 December 2021, 5pm

This homework will be graded by Zhang Qi

In this homework, we would like to look at the Bayesian Networks. You are given a Bayesian network as below. All nodes can take 2 different values: {1, 2}.


 $x_2:$

1	1	2
2		

We have to ensure that at least of the in-between nodes fall on different values
 \rightarrow To ensure that X_1 & X_6 are independent,

Question 1. Without knowing the actual value of any node, are node X_1 and X_6 independent of each other? What if we know the value of node X_5 and X_{10} ? (10 points)

Question 2. What is the effective number of parameters needed to for this Bayesian network? What would be the effective number of parameters for the same network if node X_3 , X_8 and X_9 can take 5 different values: {1, 2, 3, 4, 5}, and all other nodes can only take 4 different values: {1, 2, 3, 4}? (10 points)

Question 3. If we have the following probability tables for the nodes. Compute the following probabilities. Clearly write down all the necessary steps.

(a) Calculate the following conditional probability:

$$P(X_3 = 1 | X_4 = 2)$$

11 Qs. (8 points)

(b) Calculate the following conditional probability:

$$P(X_5 = 2 | X_2 = 1, X_{11} = 2, X_1 = 1)$$

(12 points)

(Hint: find a short answer. The values in some of the probability tables may reveal some useful information.)

\mathbf{X}_1		\mathbf{X}_2		\mathbf{X}_3		\mathbf{X}_4		\mathbf{X}_5		\mathbf{X}_6		
\mathbf{X}_1	1	2	\mathbf{X}_2	1	2	\mathbf{X}_3	1	2	\mathbf{X}_4	1	2	
1	0.5	0.5	1	0.2	0.8	1	0.3	0.7	1	0.1	0.9	
2	0.3	0.7	2	0.3	0.7	2	0.3	0.7	2	0.5	0.5	
										1	0.6	0.4

\mathbf{X}_6			\mathbf{X}_7		\mathbf{X}_8			\mathbf{X}_9		\mathbf{X}_{10}		\mathbf{X}_{11}				
\mathbf{X}_6	\mathbf{X}_7	\mathbf{X}_8	\mathbf{X}_9	1	2	\mathbf{X}_9	1	2	\mathbf{X}_{10}	1	2	\mathbf{X}_{10}	1	2		
\mathbf{X}_5	1	2	\mathbf{X}_5	1	2	1	1	1	0.8	0.2	1	0.8	0.2	1	0.7	0.3
1	0.2	0.8	1	0.8	0.2	1	1	2	0.1	0.9	2	0.8	0.2	2	0.8	0.2
2	0.3	0.7	2	0.7	0.3	1	2	1	0.9	0.1	1	0.8	0.2	2	0.8	0.2
						2	1	2	0.7	0.3	2	1	2	2	0.8	0.2
						2	1	1	0.3	0.7	2	2	1	2	0.2	0.8
						2	2	1	0.2	0.8	2	2	1	2	0.2	0.8
						2	2	2	0.9	0.1	2	2	2	2	0.8	0.2

Question 4. Now, assume we do not have any knowledge about the probability tables for the nodes in the network, but we have the following 12 observations/samples. Find a way to estimate the probability tables associated with the nodes X_7 and X_9 respectively. (10 points)

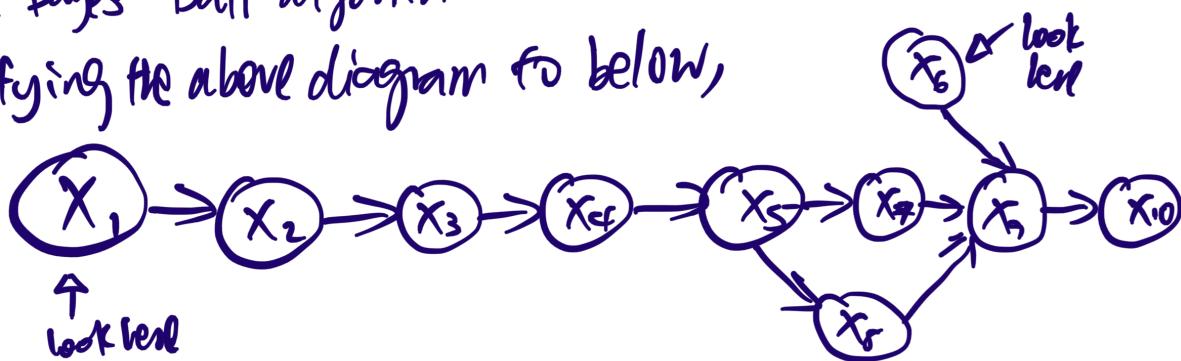
X ₁	X ₂	X ₃	X ₄	X ₅	X ₆	X ₇	X ₈	X ₉	X ₁₀	X ₁₁
1	1	2	2	2	1	1	1	2	1	1
1	2	1	1	2	1	1	1	1	1	2
2	2	2	1	2	2	1	1	1	2	1
1	1	2	1	2	1	1	2	1	2	2
1	2	1	1	1	1	2	2	2	1	1
2	2	1	2	1	2	2	1	1	1	2
2	1	2	2	1	2	1	2	2	2	1
2	2	2	1	2	1	2	2	1	2	2
1	1	1	1	2	2	1	1	1	1	1
1	1	1	1	2	1	1	1	2	1	2
1	2	1	2	2	1	2	1	1	1	2
2	2	1	2	1	2	2	2	2	1	1

Question)

Aim: X_1 & X_6 independent of each other?

We use the Bayes' Ball algorithm seen below:

Simplifying the above diagram to below,



From this diagram, there is a closed path. Hence, we can say that the ball cannot find the path from X_1 to X_6 or from X_6 to X_1 , as none of the X variables are active.

This is because with none of the observed X variables,

Path 1 from X_1 to X_6 :



Closed path

Path 2 from X_1 to X_6 :



Closed path

Given that X_9 is not observed.

\therefore - The ball cannot flow to X_6 .

\therefore - X_1 and X_6 are independent.

Part 2: With X_5 and X_{10} observed,

With X_5 known, the path is active. Hence, X_1 only need to depend on X_5

With X_5 and X_{10} known, two nodes are active. Hence, X_1 and X_6 are independent ^{along flip path}

Question 2

[Part 1]

For the same network where each node takes the value of $\{1, 2\}$, for the number of free parameters, we exclude that of the last column in each modl.

= -

$$\begin{aligned} \text{No. of} \\ \text{free parameters} &= \underbrace{(2-1)(1)}_{X_1} + \underbrace{8(2-1)(2)}_{\substack{\leftarrow 8 \text{ nodes} \\ X_2, X_3, X_4, X_5, \\ X_7, X_8, X_{10}, X_{11}}} + \underbrace{(2-1)(1)}_{X_6} + \underbrace{(2-1)(2^3)}_{X_9} \end{aligned}$$

X_9 depends on X_6, X_7, X_8

X_6	X_7	X_8		1	2
1	1	1			
1	1	2			
1	2	1			
2	2	2			

This is
just for
my sanity
check

$$= 1 + 16 + 1 + 8$$

$$= 26 \#$$

Same thing as Part 1, given new observation set of

① X_3, X_8 and X_9 taking values $\{1, 2, 3, 4, 5\}$

② The rest taking $\{1, 2, 3, 4\}$

Continue on next page!

For x_3, x_8 and x_9 ,

N.o of free parameters = $(5-1)(4) = 16$

for x_3

N.o of free parameters = $(5-1)(4) = 16$

for x_8

N.o of free parameters for x_9 = $(5-1)(4^2)(5) = 320$

$\underbrace{\quad}_{6,7}$ $\underbrace{\quad}_{\text{depends on } g}$
depends on g

For the others,

A — N.o of free parameters = $(4-1)^3 \leftarrow$ for x_1 and x_6
each

B — N.o of free parameters = $(4-1)(4)^3 \leftarrow$ for x_2, x_5, x_7, x_{11}
each

C — N.o of free parameters = $(4-1)(5) = 15 \leftarrow$ x_4, x_{10}
each

Total

$$\text{No. of effective} = 2\textcircled{C} + 4\textcircled{B} + 2\textcircled{A} + 16 + 16 + 320$$

$$\begin{aligned}\text{Parameters} &= 30 + 48 + 6 + 16 + 16 + 320 \\ &= 436\end{aligned}$$

Question 3

$$(a) P(X_3=1 | X_4=2) = \frac{P(X_3=1, X_4=2)}{\sum_{b \in \{1,2\}} P(X_3=b, X_4=2)}$$

$$P(X_3=b, X_4=2)$$

$$= \sum_{a \in \{1,2\}} \sum_{d \in \{1,2\}} P(X_1=a, X_2=d, X_3=b, X_4=2)$$

$$= \sum_{a \in \{1,2\}} \sum_{d \in \{1,2\}} P(X_1=a) P(X_2=d | X_1=a) P(X_3=b | X_2=d, X_4=2)$$

$$= P(X_3=b) P(X_4=2 | X_3=b) \leftarrow \text{we can frame and know that } X_4 \text{ is only dependent on } X_3 \text{ being observed.}$$

$$\therefore \sum_{b \in \{1,2\}} P(X_3=b, X_4=2)$$

$$= [P(X_3=1) P(X_4=2 | X_3=1)] + [P(X_3=2) \cdot P(X_4=2 | X_3=2)]$$

next page . . .

$$P(X_3 = b) \underset{\substack{z \in \{1, 2\} \\ a \in \{1, 2\}}}{=} \sum_{a \in \{1, 2\}} P(X_2 = a) \cdot P(X_3 = b | X_2 = a)$$

$$P(X_2 | X_1 = z)$$

We can use the idea of the open & close brackets to determine independence!

$$= \sum_{a \in \{1, 2\}} P(X_3 = b | X_2 = a) \cdot P(X_2 = a)$$

$$\begin{aligned} \therefore P(X_3 = 1) &= 0.3 [(0.2 \times 0.5) + (0.3 \times 0.5)] + \\ &\quad 0.3 [(0.8 \times 0.5) + (0.7 \times 0.5)] \\ &= 0.3 \leftarrow \text{we can see that } X_3 \text{ does need} \\ &\quad \text{to involve } X_1 \text{ and } X_2 \text{ in this case.} \end{aligned}$$

Using the same discovery,

$$P(X_3 = 2) = 0.7$$

$$\begin{aligned} \therefore \sum_{b \in \{1, 2\}} P(X_3 = b, X_4 = 2) &= 0.3 \times (0.9) + \\ &\quad 0.7 \times (0.5) \\ &= \frac{31}{50} = 0.62 \end{aligned}$$

$$P(X_3 = 1, X_4 = 2) = 0.3 [0.9]$$

$$\therefore P(X_3 = 1 | X_4 = 2) = \frac{0.27}{0.62} = \frac{27}{62} \#$$

$$(b) P(X_5=2 | X_2=1, X_{11}=2, X_1=1)$$

Same thing using Bayes theorem,

$$= \frac{P(X_5=2, X_2=1, X_{11}=2, X_1=1)}{P(X_2=1, X_{11}=2, X_1=1)}$$

We identify the close and open paths and split accordingly:

X_5 is given in terms of observation

We also identify that it's a chain. Hence, we can apply the chain property stated in the lecture notes!

Since X_5 is an observed event,

$$\begin{aligned} & P(X_6, \dots, X_{11} | X_1, X_2, X_3, X_4, X_5) \\ = & P(X_6, \dots, X_{11} | X_5) \\ P(X_1, X_2, X_5, X_{11}) &= \sum_{\substack{X_3, X_4, X_6, X_7, \\ X_8, X_9, X_{10}}} P(X_1, \dots, X_{11}) \\ &= \sum_{\substack{X_3, X_4, \\ X_5, X_7 \\ X_8, X_9, X_{10}}} P(X_1, \dots, X_5) \left(P(X_6, \dots, X_{11} | X_5) \right) \end{aligned}$$

next page ...

$$P(X_1, X_2, X_5, X_{11})$$

$$= \sum_{X_3, X_4} P(X_1, \dots, X_5) \cdot \sum_{\substack{X_6, X_7, \\ X_8, X_9, \\ X_{10}}} P(X_6, \dots, X_{11} | X_5)$$

let's eyeball and use the starting similarity in the table of

values of $X_{10} \Rightarrow X_1$ to X_9 are independent of X_{10} we employ the

$$= \left(\sum_{X_3, X_4} \underbrace{P(X_5 | X_4, \dots, X_1) \cdot P(X_4 | X_3, X_2, X_1)}_{\text{same trick as part a.}} \cdot \underbrace{P(X_2 | X_1) \cdot P(X_1)}_{\text{for each node has their set of values.}} \right) \cdot \left(\sum_{X_{10}} P(X_{11}, X_{10}) \right)$$

$$= \left(\sum_{X_3, X_4} P(X_5 | X_4) \cdot P(X_4 | X_3) \cdot P(X_2 | X_1) \cdot P(X_1) \right)$$

$$\sum_{X_{10}} P(X_{11} | X_{10}) P(X_{10})$$

$$= \overline{\sum_{X_3, X_4} P(X_5 | X_4) \cdot P(X_4 | X_3) \cdot P(X_3) \cdot P(X_2 | X_1) \cdot P(X_1)} \cdot P(X_{10})$$

$$P(X_1=1, X_2=1, X_5=2, X_{11}=2)$$

(continue next page!)

Note: The method is adapted from Ang Song Gee.

$$P(X_1=1, X_2=1, X_5=2, X_{11}=2)$$

$$= \left[P(X_5=2 | X_4=1) \cdot P(X_4=1 | X_3=1) \cdot P(X_3=1) + \right. \\ \left. P(X_5=2 | X_4=1) \cdot P(X_4=1 | X_3=2) \cdot P(X_3=2) + \right. \\ \left. P(X_5=2 | X_4=2) \cdot P(X_4=2 | X_3=1) \cdot P(X_3=1) + \right. \\ \left. P(X_5=2 | X_4=2) \cdot P(X_4=2 | X_3=2) \cdot P(X_3=2) \right] \cdot \\ P(X_2=1 | X_1=1) \cdot P(X_1=1) \cdot$$

$$\left[P(X_{11}=2 | X_{10}=1) \cdot P(X_{10}=1) + \right. \\ \left. P(X_{11}=2 | X_{10}=2) \cdot P(X_{10}=2) \right]$$

$$= \left[\begin{matrix} 0.5 \cdot 0.1 \cdot 0.3 + \\ 0.5 \cdot 0.5 \cdot 0.7 + \\ 0.4 \cdot 0.9 \cdot 0.3 + \\ 0.4 \cdot 0.5 \cdot 0.7 \end{matrix} \right] \cdot 0.2 \cdot 0.5 \cdot \left[\begin{matrix} 0.3 \cdot 0.8 + \\ 0.2 \cdot 0.2 \end{matrix} \right]$$

$$= 0.012264$$

$$P(X_2, X_{11}, X_1) = P(X_1) \cdot P(X_2 | X_1) \cdot \\ \sum_{X_{10}} P(X_{11} | X_{10}) \cdot P(X_{10})$$

Same thing,

$$P(X_2=1, X_{11}=2, X_1=1) = P(X_1=1) \cdot P(X_2=1 | X_1=1) \cdot \\ \cdot \sum P(X_{11}=2 | X_{10}) \cdot P(X_{10})$$

$$= 0.5 \cdot 0.2 \cdot [0.3 \cdot 0.8 + 0.2 \cdot 0.2]$$

$$= 0.020$$

Next page

$$\therefore P(X_5=2 | X_1=1, X_2=1, X_{11}=2) \\ = \frac{0.012264}{0.028} = 0.438$$

Question 4

For node X_7 , we notice the following:

Direct connection is node X_5

To form the probability table, we calculate the maximum likelihood parameter using the following formula to calculate each probability table of nodes X_7 and X_9 individually.

$$\hat{\theta}_i(x_i | x_{pa_i}) = \frac{\text{Count}((x_i, x_{pa_i})) \text{in } D}{\text{Count}((x_{pa_i}) \text{in } D)}, x_i \in \{1, \dots, r\}$$

$$\hat{\theta}_7(x_7 | x_5) = \frac{\text{Count}((x_7, x_5)) \text{in } D}{\text{Count}((x_5) \text{in } D)}$$

$x_5 \rightarrow x_7$ { what we are looking at. }

$$\hat{\theta}_7(x_7=1 | x_5=1) = \frac{1}{4}$$

$$\hat{\theta}_7(x_7=2 | x_5=2) = \frac{2}{8}$$

$$= \frac{1}{4}$$

$$\hat{\theta}_7(x_7=1 | x_5=2) = \frac{6}{8} = \frac{3}{4}$$

$$\hat{\theta}_7(x_7=2 \mid x_5=1) = \frac{3}{4}$$

\therefore For x_7

x_5	x_7	
	1	2
1	0.25	0.75
2	0.75	0.25

For x_9 , we need to take into account x_6 , x_7 and x_8

$$\hat{\theta}_9(x_9=1 \mid x_6=1, x_7=1, x_8=1)$$

$$= \frac{1}{3}$$

$$\hat{\theta}_9(x_9=1 \mid x_6=1, x_7=1, x_8=2)$$

$$= \frac{1}{1} = 1$$

$$\hat{\theta}_9(x_9=1 \mid x_6=1, x_7=2, x_8=1)$$

$$= \frac{1}{1} = 1$$

$$\hat{\theta}_9(x_9=1 \mid x_6=1, x_7=2, x_8=2)$$

$$= \frac{1}{2}$$

$$\hat{\theta}_9(X_9=1 \mid X_6=2, X_7=1, X_8=1)$$

$$= \frac{1+1}{2} = 1$$

$$\hat{\theta}_9(X_9=1 \mid X_6=2, X_7=1, X_8=2)$$

$$= \frac{0}{1} = 0$$

$$\hat{\theta}_9(X_9=1 \mid X_6=2, X_7=2, X_8=1)$$

$$= \frac{1+1}{1+1} = 1$$

$$\hat{\theta}_9(X_9=1 \mid X_6=2, X_7=2, X_8=2)$$

$$= \frac{0}{1} = 0$$

$$\hat{\theta}_9(X_9=2 \mid X_6=1, X_7=1, X_8=1)$$

$$= \frac{1+1}{1+1+1} = \frac{2}{3}$$

$$\hat{\theta}_9(X_9=2 \mid X_6=1, X_7=1, X_8=2)$$

$$= \frac{0}{1} = 0$$

$$\hat{\theta}_9(X_9=2 \mid X_6=1, X_7=2, X_8=1)$$

$$= \frac{0}{1} = 0$$

$$\hat{\theta}_9(X_9=2 \mid X_6=1, X_7=2, X_8=2)$$

$$= \frac{1}{1+1} = \frac{1}{2}$$

$$\hat{\theta}_9(X_9=2 \mid X_6=2, X_7=1, X_8=1)$$

$$= \frac{0}{1+1} = 0$$

$$\hat{\theta}_9(X_9=2 \mid X_6=2, X_7=1, X_8=2)$$

$$= \frac{1}{1} = 1$$

$$\hat{\theta}_9(X_9=2 \mid X_6=2, X_7=2, X_8=1)$$

$$= \frac{0}{1} = 0$$

$$\hat{\theta}_9(X_9=2 \mid X_6=2, X_7=2, X_8=2)$$

$$= \frac{1}{1} = 1$$

X_6	X_7	X_8	X_9
1	1	1	$\frac{1}{3}$
1	1	2	0
1	2	1	0
1	2	2	$\frac{1}{2}$
2	1	1	0
2	1	2	1
2	2	1	0
2	2	2	1

entries
 $2^3 \times 2$
 $= 16$