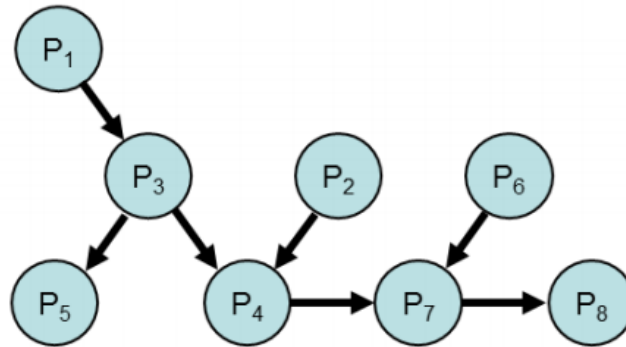
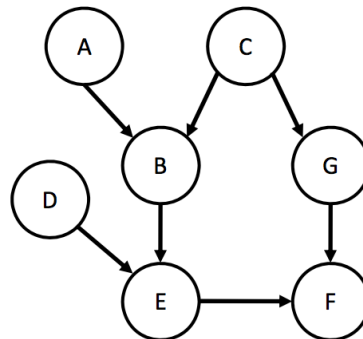


1 Bayesian Network Problems



1. Given the Bayesian Network above, determine:

- (a) if P1 and P5 are independent of P6 given P8
FALSE, the path through P3, P4 and P7 is not blocked; neither P1 and P6 or P5 and P6 are d-separated.
- (b) if P2 is independent of P6 given no information
TRUE, the path is blocked by node P7.
- (c) if P1 is independent of P2 given P8
FALSE, P1 and P2 converge on P4 and the path between them is un-blocked by P8.
- (d) if P1 is independent of P2 and P5 given P4
FALSE, P4 unblocks the path of information from P2 and P3 is not blocked.

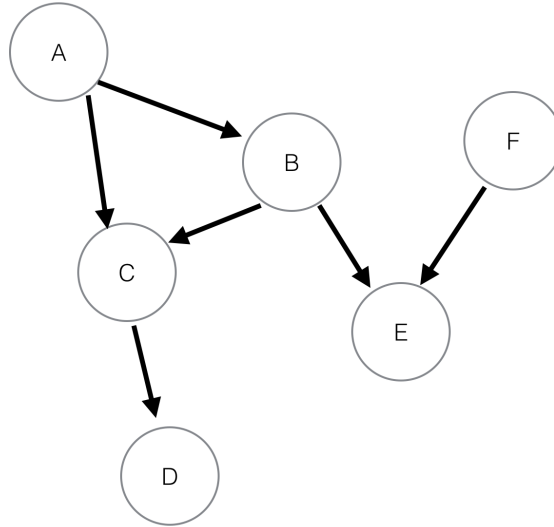


2. Given the Bayesian Network above, determine if:

- (a) A is independent of C given F.
Answer: False. There is an unblocked (or not d-separated) path from A to B to E, and then thru F to G to C. Note that without information about F, the path from E to G is blocked.
- (b) G is independent of D given E.
Answer: False. There is an unblocked (or not d-separated) path from D to E to B, and then to G.

(c) C is independent of D.

Answer: True. The fact that we have no information about E d-separates the path from D to B. No information about F d-separates E and G. So information about D is d-separated from paths to C both via F and E.



Given this network, calculate $P(B|D = \text{false})$, $P(B|E = \text{true})$ and $P(B|F = \text{false})$.

Answer Part 1:

$$P(B|D = \text{false}) = \frac{\sum_A \sum_C \sum_E \sum_F P(A, B, C, D = \text{false}, E, F)}{\sum_A \sum_B \sum_C \sum_E \sum_F P(A, B, C, D = \text{false}, E, F)}$$

$P(A, B, C, D = \text{false}, E, F) = P(A)P(B|A)P(C|A, B)P(D = \text{false}|C)P(E|F, B)P(F)$ so

$$\begin{aligned} & \sum_A \sum_C \sum_E \sum_F P(A, B, C, D = \text{false}, E, F) \\ &= \sum_A \sum_C \sum_E \sum_F P(A)P(B|A)P(C|A, B)P(D = \text{false}|C)P(E|F, B)P(F) \\ &= \sum_A P(A)P(B|A) \sum_C P(C|A, B)P(D = \text{false}|C) \sum_F P(F) \sum_E P(E|F, B) \end{aligned}$$

Note that $\sum_E P(E|F, B)$ results in a table of 1s and so multiplying this by $\sum_F P(F)$ will result in 1s. Both of E and F are not relevant to the query (and can be identified by the relevance algorithm presented in class). We therefore focus on eliminating C and A .

$$\text{Eliminate C: } f_1(A, B) = \sum_C P(C|A, B)P(D = \text{false}|C)$$

$$\begin{aligned} f_1(a, b) &= P(c|a, b)P(D = \text{false}|c) + P(-c|a, b)P(D = \text{false}|-c) \\ f_1(a, -b) &= P(c|a, -b)P(D = \text{false}|c) + P(-c|a, -b)P(D = \text{false}|-c) \\ f_1(-a, b) &= P(c|-a, b)P(D = \text{false}|c) + P(-c|-a, b)P(D = \text{false}|-c) \\ f_1(-a, -b) &= P(c|-a, -b)P(D = \text{false}|c) + P(-c|-a, -b)P(D = \text{false}|-c) \end{aligned}$$

$$\text{Eliminate A: } f_2(B) = \sum_A P(A)P(B|A)f_1(A, B)$$

$$f_2(b) = P(a)P(b|a)f_1(a, b) + P(-a)P(b|-a)f_1(-a, b)$$

$$f_2(-b) = P(a)P(-b|a)f_1(a, -b) + P(-a)P(-b|-a)f_1(-a, -b)$$

$$\text{Normalize: } P(B|D = \text{false}) = \text{normalize}(f_2(B)) = f_2(B)/(f_2(b) + f_2(-b))$$

Answer Part 2:

$$P(B|E = \text{true}) = \frac{\sum_A \sum_C \sum_D \sum_F P(A, B, C, D, E = \text{true}, F)}{\sum_A \sum_B \sum_C \sum_D \sum_F P(A, B, C, D, E = \text{true}, F)}$$

$$P(A, B, C, D, E = \text{true}, F) = P(A)P(B|A)P(C|A, B)P(D|C)P(E = \text{true}|F, B)P(F) \text{ so}$$

$$\begin{aligned} & \sum_A \sum_C \sum_D \sum_F P(A, B, C, D, E = \text{true}, F) \\ &= \sum_A \sum_F \sum_C \sum_D P(A)P(B|A)P(C|A, B)P(D|C)P(E = \text{true}|F, B)P(F) \\ &= \sum_A P(A)P(B|A) \sum_F P(E = \text{true}|F, B)P(F) \sum_C P(C|A, B) \sum_D P(D|C) \end{aligned}$$

Note that $\sum_D P(D|C)$ results in a table of 1s and $\sum_C P(C|A, B)$ is also a table of 1s. Both of C and D are not relevant to the query (and can be identified by the relevance algorithm presented in class). We therefore focus on eliminating A and F .

$$\text{Eliminate F: } f_1(B) = \sum_F P(E = \text{true}|F, B)P(F)$$

$$\begin{aligned} f_1(b) &= P(e|f, b)P(f) + P(e|-f, b)P(-f) \\ f_1(-b) &= P(e|f, -b)P(f) + P(e|-f, -b)P(-f) \end{aligned}$$

$$\text{Eliminate A: } f_2(B) = \sum_A P(A)P(B|A)$$

$$\begin{aligned} f_2(b) &= P(b|a)P(a) + P(b|-a)P(-a) \\ f_2(-b) &= P(-b|a)P(a) + P(-b|-a)P(-a) \end{aligned}$$

$$\text{Normalize: } P(B|E = \text{true}) = \text{normalize}(f_1(B)f_2(B)) = f_1(B)f_2(B)/(f_1(b)f_2(b) + f_1(-b)f_2(-b))$$

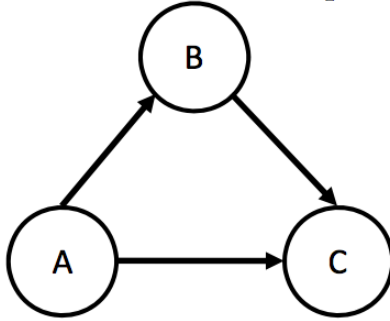
Answer Part 3:

$$P(B|F = \text{false}) = \frac{\sum_A \sum_C \sum_D \sum_E P(A, B, C, D, E, F = \text{false})}{\sum_A \sum_B \sum_C \sum_D \sum_E P(A, B, C, D, E, F = \text{false})}$$

Note however that F is d-separated from B by E . This means $P(B|F) = P(B)$ and can be computed directly from input CPTs.

$$P(B) = \sum_A P(A, B) = \sum_A P(B|A) * P(A)$$

3. Given the Bayesian Network Below:



$P(A = true) = 0.75$	$P(C = true A = true, B = true) = 0.8$
	$P(C = true A = true, B = false) = 0.8$
	$P(C = true A = false, B = true) = 0.25$
	$P(C = true A = false, B = false) = 0.25$
$P(B = true A = true) = 0.9$	
$P(B = true A = false) = 0.8$	

- (a) Are any variables in the graph conditionally independent of each other? Why or why not?

Answer: Even tho there is a line between C and B, C and B are independent given A. This is because $P(C|A, B) = P(C|A)$ for all combinations of A,B and C. This should tell you that while lack of a line can indicate independences (or conditional independences) between variables, presence of a line does not necessarily indicate independences (or conditional independences).

- (b) Calculate $P(A = true|B = true, C = true)$

Answer:

$$P(A = true|B = true, C = true) = P(A = true, B = true, C = true)/P(B = true, C = true)$$

$$= P(A = true, B = true, C = true)/\sum_A P(A, B = true, C = true)$$

$$= P(C = true|A = true, B = true) * P(B = true|A = true) * P(A = true)/\sum_A P(C = true|A, B = true) * P(B = true|A) * P(A)$$

$$= (0.75 * 0.9 * 0.8)/((0.75 * 0.9 * 0.8) + (0.25 * 0.8 * 0.2)) = 0.92$$

Note that this can be simplified if you substitute $P(C|A, B) = P(C|A)$ in the equations above.