

Question 1: Designing a Bayesian Network

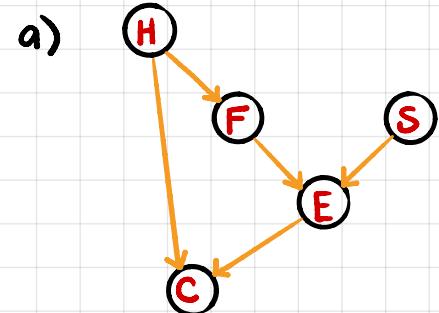
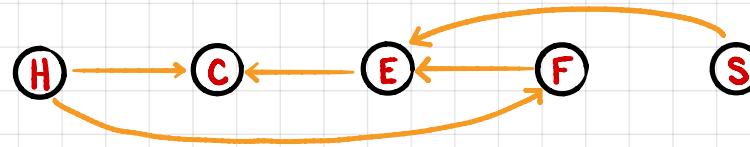
H - hot day

C - Marv is content

E - Marv eats ≥1 item

F - Marv catches a fish

S - Marv steals a sandwich.



b) This network is not a polytree due to the undirected cycle between the nodes H, F, E and C.

c) $P(F|H) = x$
 $P(F=1|H=0) = y$

		F=0	F=1
H=0	1-y	y	
H=1	1-x	x	

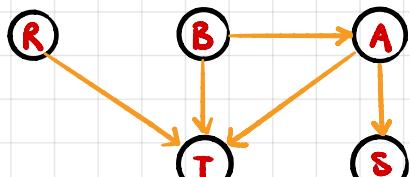
d) $P(E=1|F=1) = 1.0$
 $P(E=1|S=1) = 0.5$
 $P(E=1|S=0, F=0) = 0$

	E=1	E=0
F=0 S=0	0.0	1.0
F=1 S=0	1.0	0.0
F=1 S=1	1.0	0.0
F=0 S=1	0.5	0.5

e) $P(H=1|C=1) = P(H=1, C=1) / P(C=1)$
 $= \sum_{f,e,s} P(H=1, F=f, S=s, E=e, C=1) / \sum_{h,f,e,s} P(H=h, F=f, S=s, E=e, C=1)$

Question 2 : Inference in Bayesian Networks

R: rush hour
 B: bad weather
 A: accident
 T: traffic jam
 S: sirens



$$P(B=1) = P(b) = 0.4$$

$$P(R=1) = P(r) = 0.2$$

$$P(T|r, b, a) = 0.98$$

$$P(T|r, \neg b, a) = 0.9$$

$$P(T|r, b, \neg a) = 0.88$$

$$P(T|r, \neg b, \neg a) = 0.85$$

$$P(T|\neg r, b, a) = 0.5$$

$$P(T|\neg r, b, \neg a) = 0.4$$

$$P(T|\neg r, \neg b, a) = 0.6$$

$$P(T|\neg r, \neg b, \neg a) = 0.05$$

Recall the following rules :

- $P(X|Y) = P(Y|X) P(X) / P(Y)$
- $P(Y) = P(Y|X) P(X) + P(Y|\neg X) P(\neg X)$
- $P(X|Y) = P(X, Y) / P(Y)$
- $P(X_1, \dots, X_n) = \prod_{i=1}^n P(X_i | \text{parent}(X_i))$

$$a) P(a|\neg r) = P(a|r)P(\neg r)$$

$$= P(a)P(r)$$

$$P(a) = P(a|b)P(b) + P(a|\neg b)P(\neg b)$$

$$= (0.7)(0.4) + (0.2)(0.6)$$

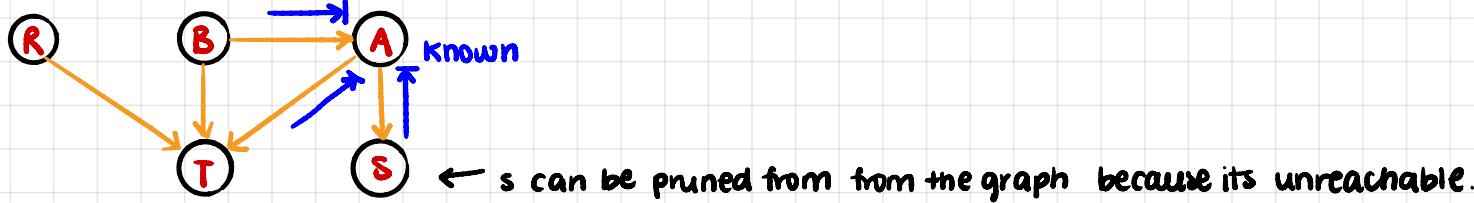
$$= 0.28 + 0.12$$

$$= 0.4$$

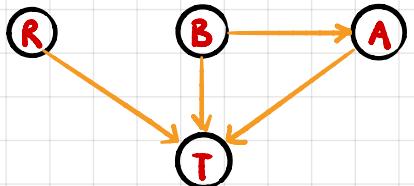
$$= P(a)P(r) = (0.4)(0.8) = 0.32$$

$$b) P(b,a) = P(b|a)P(a) = P(a|b)P(b) = (0.7)(0.4) = 0.28$$

c) use Bayes ball to see what nodes can be pruned.



we then obtain the following graph :



$$d) P(b|a) = P(a|b)P(b) / P(a)$$

$$P(a) = P(a|b)P(b) + P(a|\neg b)P(\neg b)$$

$$= (0.7)(0.4) + (0.2)(0.6)$$

$$= 0.28 + 0.12$$

$$= 0.4$$

$$P(b|a) = \frac{0.7 \times 0.4}{0.4} = 0.7$$

Question 3 : Variable elimination

$P(T|b)$, where T is the query variable
 we are given the variable ordering : S, A, R, T

We need to initialize an active factor list with the conditional probability distributions in the Baye's net.
 If we look at our graph we obtain: $P(R) P(T|R, A) P(A) P(S|A)$

Step 1: Eliminate S $\Rightarrow m_S(A) = \sum_S P(S|A)$
 List: $P(R) P(T|R, A) P(A) m_S(A)$

Step 2: Eliminate A $\Rightarrow m_A(T, R) = \sum_A P(A) P(T|R, A) m_S(A)$
 List: $P(R) m_A(T, R)$

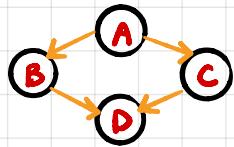
Step 3: Eliminate R $\Rightarrow m_R(T) = \sum_R P(R) m_A(T, R)$
 List: $m_R(T)$

$$\begin{aligned} \text{Now } T=1 \Rightarrow P(T|b) &= P(T|b)m_R(T) \\ &= P(T|b) \sum_R P(R) \sum_A P(A) P(T|R, A) m_S(A) \\ &= P(T|b) \sum_R P(R) \sum_A P(A) P(T|R, A) \sum_S P(S|A) \\ &= P(T|b) \sum_R \sum_A P(T|R, A) \\ &= P(T|b) \cdot \text{MAP}_{R,A} P(T=1|R, b=1, a) \\ &= (0.98)(0.57) \\ &= 0.56 \end{aligned}$$

1. Pick a variable ordering with Y (query variable) at the end of the list.
2. Initialize the active factor list with the conditional probability distributions (tables) in the Bayes net.
3. Add to the active factor list the evidence potentials $\delta(e_j, e_i)$ for all evidence variables E.
4. For $i=1..n$
 1. Take the next variable X_i from the ordering.
 2. Take all the factors that have X_i as an argument off the active factor list, and multiply them, then sum over all values of X_i , creating a new factor m_{X_i} .
 3. Put m_{X_i} on the active factor list.

Question 4: Learning with Bayesian Networks

Bernoulli distribution



a) i. $\theta_A = P(A)$
 $\theta_B = P(B)$
 $\theta_C = P(C)$
 $\theta_D = P(D)$

ii Recall that the variables are distributed according to a Bernoulli distribution and thus we apply MLE to the Bernoulli model we obtain:

the likelihood: $L(\theta|D) = \theta^x (1-\theta)^{n-x}$ when $n = \text{total # instances}$
 $x = \text{instances of query}$

the log-likelihood: $\log L(\theta|D) = x \log \theta + (n-x) \log (1-\theta)$

taking the derivative of the log-likelihood and set it to 0: $\frac{d}{d\theta} \log L(\theta|D) = \frac{x}{\theta} - \frac{(n-x)}{(1-\theta)} = 0$

which then lets us obtain $\theta = x/n$ which we then apply to this problem

$$P(A) = 60/144$$

$$P(B) = 90/144$$

$$P(C) = 112/144$$

$$P(D) = 61/144$$

iii give the MAP estimate for each parameter after applying Laplace, in Bernoulli modes we use the following:

$$\theta = x+1 / n+2 \quad \text{as we assume we have seen each possibility at least once.}$$

then we obtain the following

MAP

$$A=0$$

$$B=1$$

$$C=1$$

$$D=0$$

$$P(A) = 61/146 = 0.418$$

$$P(B) = 91/146 = 0.623$$

$$P(C) = 113/146 = 0.774$$

$$P(D) = 62/146 = 0.425$$

b)

i. $\theta_A = N_A=1 / 144$
 $= 60 / 144$

$$\theta_{D|B=0,C=0} = N_{D=1, C=0, B=0} / N_{C=0, B=0}$$

$$= 4/7$$

$$\theta_{B|A=0} = N_{B=1, A=0} / N_{A=0}$$

$$= 57/84$$

$$\theta_{D|B=1,C=0} = N_{D=1, C=0, B=1} / N_{B=1, C=0}$$

$$= 11/25$$

$$\theta_{B|A=1} = N_{B=1, A=1} / N_{A=1}$$

$$= 33/60$$

$$\theta_{D|B=1,C=1} = N_{D=1, C=1, B=1} / N_{B=1, C=1}$$

$$= 20/65$$

$$\theta_{C|A=0} = N_{C=1, A=0} / N_{A=0}$$

$$= 62/84$$

$$\theta_{D|B=0,C=1} = N_{D=1, C=1, B=0} / N_{B=0, C=1}$$

$$= 26/47$$

$$\theta_{C|A=1} = N_{C=1, A=1} / N_{A=1}$$

$$= 50/60$$

E-step

$$w_{Bs_1=0} = P(Bs_1=0 | As_1)$$

$$= P(B=0 | A=1)$$

$$= 27/60$$

$$= 0.45$$

$$w_{Bs_1=1} = P(Bs_1=1 | As_1)$$

$$= P(B=1 | A=1)$$

$$= 33/60$$

$$= 0.55$$

$$w_{Ds_1=0} = P(Ds_1=0 | Bs_1, Cs_1)$$

$$= P(D=0 | B=0, C=0) w_{Bs_1=0} + P(D=0 | B=0, C=1) w_{Bs_1=1}$$

$$= (21/47)(0.45) + (45/65)(0.55)$$

$$= 0.58$$

$$w_{Ds_1=1} = P(Ds_1=1 | Bs_1, Cs_1)$$

$$= P(D=1 | B=0, C=1) w_{Bs_1=0} + P(D=1 | B=0, C=0) w_{Bs_1=1}$$

$$= (26/47)(0.45) + (20/65)(0.55)$$

$$= 0.42$$

ii M-Step

$$\theta_A = N_A(1:146) / 146 \\ = 62 / 146$$

$$\theta_{B|A=0} = N_B=1, A=0 (1:144, 146) + w_{BS_1=1} / N_A=0 (1:146) \\ = 57.55 / 48$$

$$\theta_{B|A=1} = N_B=1, A=1 (1:144, 146) + w_{BS_1=1} / N_A=1 (1:146) \\ = 34.55 / 62$$

$$\theta_{C|A=0} = N_C=1, A=0 (1:146) / N_A=0 (1:146) \\ = 62 / 84$$

$$\theta_{C|A=1} = N_C=1, A=1 (1:146) / N_A=1 (1:146) \\ = 51 / 62$$

$$\theta_{D|B=0, C=0} = N_D=1, B=0, C=0 (1:144, 146) + w_{BS_1=0} + w_{DS_1=1} / N_B=0, C=0 (1:144, 146) + w_{BS_1=0} \\ = 5.03 / 7.45$$

$$\theta_{D|B=1, C=0} = N_D=1, B=1, C=0 (1:144, 146) + w_{BS_1=1} + w_{DS_1=1} / N_B=1, C=0 (1:144, 146) + w_{BS_1=1} \\ = 12.13 / 26.55$$

$$\theta_{D|B=0, C=1} = N_D=1, B=0, C=1 (1:144, 146) + w_{BS_1=0} + w_{DS_1=1} / N_B=0, C=1 (1:144, 146) + w_{BS_1=0} \\ = 27.03 / 47.45$$

$$\theta_{D|B=1, C=1} = N_D=1, B=1, C=1 (1:144, 146) + w_{BS_1=1} + w_{DS_1=1} / N_B=1, C=1 (1:144, 146) + w_{BS_1=1} \\ = 21.13 / 65.55$$

iii E-Step now estimate using new weights & obtain new weights

$$w_{BS_1=0} = P(B_{S_1}=0 | A_{S_1}) \\ = P(B=0 | A=1) \\ = 0.44$$

$$w_{BS_1=1} = P(B_{S_1}=1 | A_{S_1}) \\ = P(B=1 | A=1) \\ = 0.56$$

$$w_{DS_1=0} = P(D_{S_1}=0 | B_{S_1}, C_{S_1}) \\ = P(D=0 | B=0, C=1) w_{BS_1=0} + P(D=0 | B=1, C=1) w_{BS_1=1} \\ = (0.43)(0.44) + (0.68)(0.56) \\ = 0.57$$

$$w_{DS_1=1} = P(D_{S_1}=1 | B_{S_1}, C_{S_1}) \\ = P(D=1 | B=0, C=1) w_{BS_1=0} + P(D=1 | B=1, C=1) w_{BS_1=1} \\ = (0.57)(0.44) + (0.32)(0.56) \\ = 0.43$$