

HW4

Answer: Subd

$$1) P(K) = \gamma \quad P(L) = 1 - \gamma \quad P_K(x; \lambda) = \frac{2^x \lambda^x e^{-2\lambda}}{x!} \quad P_L(x; \mu) = \frac{\mu^x e^{-\mu}}{x!}$$

$$(a) \mathcal{L}(\text{Dataset}) = \prod_{i \in K} \gamma P_K(x^{(i)} | z=K) \prod_{i \in L} (1-\gamma) P_L(x^{(i)} | z=L)$$

Likelihood

$$\mathcal{L}(\text{Dataset}) = \prod_{i \in K} \gamma \frac{2^{x^{(i)}} \lambda^{x^{(i)}} e^{-2\lambda}}{x^{(i)}!} \prod_{i \in L} (1-\gamma) \frac{\mu^{x^{(i)}} e^{-\mu}}{x^{(i)}!}$$

(b)

$$\ln(\mathcal{L}(\text{Dataset})) = \ln \prod_{i \in K} \gamma \frac{2^{x^{(i)}} \lambda^{x^{(i)}} e^{-2\lambda}}{x^{(i)}!} \prod_{i \in L} (1-\gamma) \frac{\mu^{x^{(i)}} e^{-\mu}}{x^{(i)}!}$$

$$= \sum_{i \in K} \ln(\gamma) + x^{(i)} \ln 2\lambda - 2\lambda - \ln(x^{(i)}!) + \sum_{i \in L} \ln(1-\gamma) + x^{(i)} \ln \frac{\mu}{2} - \frac{\mu}{2} - \ln x^{(i)}!$$

$$= \left\{ n_K \ln(\gamma) + m_K \ln(2\lambda) - 2\lambda n_K - S_K + n_L \ln(1-\gamma) + m_L \ln\left(\frac{\mu}{2}\right) - \frac{\mu}{2} n_L - S_L \right\}$$

(c)

$$\frac{\partial}{\partial \gamma} \ln(\mathcal{L}(\text{Dataset})) = \frac{n_K}{\gamma} + \frac{n_L}{1-\gamma} = 0$$

$$n_K(1-\gamma) = n_L \gamma \rightarrow \frac{n_K}{n_K + n_L} = \gamma$$

$$n_K = 4$$

$$n_L = 6$$

$$\gamma = \frac{4}{10} = \frac{2}{5}$$

$$1-\gamma = \frac{3}{5}$$

$$\frac{\partial}{\partial \lambda} \ln(\mathcal{L}(\text{Dataset})) = \frac{m_K}{\lambda} - 2n_K = 0$$

$$\frac{m_K}{2n_K} = \lambda$$

$$\lambda = \frac{\sum_{i \in K} x^{(i)}}{2(4)} = \frac{23}{8}$$

$$\frac{\partial}{\partial \mu} \ln(\mathcal{L}(\text{Dataset})) = \frac{m_L}{\mu} - \frac{n_L}{2} = 0$$

$$\frac{2m_L}{n_L} = \mu = \frac{2 \sum_{i \in L} x^{(i)}}{n_L} = \frac{2 \cdot 21}{6} = \frac{21}{3} = 7$$

$$\mu = 7$$

2 Expectation Maximization

(a) Use Bayes Rule $\rightarrow P(z^{(i)}=k | x^{(i)}; \theta^{(i)}) = \frac{P(\bar{x}^{(i)} | z^{(i)}=k; \bar{\theta}^{(i)}) P(z^{(i)}=k | \bar{\theta}^{(i)})}{P(\bar{x}^{(i)} | \bar{\theta}^{(i)})}$

$P(\bar{x}^{(i)} | \bar{\theta}^{(i)}) = P(\bar{x}^{(i)} | z^{(i)}=A; \bar{\theta}^{(i)}) P(z^{(i)}=A | \bar{\theta}^{(i)}) + P(\bar{x}^{(i)} | z^{(i)}=B; \bar{\theta}^{(i)}) P(z^{(i)}=B | \bar{\theta}^{(i)})$

Since: $P(z^{(i)}=A | \bar{\theta}^{(i)}) = P(z^{(i)}=B | \bar{\theta}^{(i)}) = \frac{1}{2}$

$P(z^{(i)}=k | \bar{x}^{(i)}; \bar{\theta}^{(i)}) = \frac{P(\bar{x}^{(i)} | z^{(i)}=k; \bar{\theta}^{(i)}) \frac{1}{2}}{P(\bar{x}^{(i)} | z^{(i)}=A; \bar{\theta}^{(i)}) \frac{1}{2} + P(\bar{x}^{(i)} | z^{(i)}=B; \bar{\theta}^{(i)}) \frac{1}{2}} = \frac{P(\bar{x}^{(i)} | z^{(i)}=k; \bar{\theta}^{(i)})}{P(\bar{x}^{(i)} | z^{(i)}=A; \bar{\theta}^{(i)}) + P(\bar{x}^{(i)} | z^{(i)}=B; \bar{\theta}^{(i)})}$

Sub in $P(\bar{x}^{(i)} | z^{(i)}=k; \bar{\theta}^{(i)}) = \theta_{k_s}^{s_i} \theta_{k_c}^{c_i} \theta_{k_r}^{r_i}$

$P(z^{(i)}=k | \bar{x}^{(i)}; \bar{\theta}^{(i)}) = \frac{\theta_{k_s}^{s_i} \theta_{k_c}^{c_i} \theta_{k_r}^{r_i}}{\theta_{A_s}^{s_i} \theta_{A_c}^{c_i} \theta_{A_r}^{r_i} + \theta_{B_s}^{s_i} \theta_{B_c}^{c_i} \theta_{B_r}^{r_i}}$

(b) $\bar{\theta}^{(0)} = [5, 3, 2, 2, 3, 5]$ $M^1 \rightarrow s_1=4, c_1=2, r_1=4$ $P(z^{(1)}=A | x^{(1)}; \bar{\theta}^{(0)}) = \frac{.5^4 \cdot 3^2 \cdot 2^4}{.5^4 \cdot 3^2 \cdot 2^4 + .2^4 \cdot 3^4 \cdot 5^4} = .5$ $P(z^{(1)}=B | x^{(1)}; \bar{\theta}^{(0)}) = 1 - .5 = .5$

$z_{(1)}^{(1)} = A$ He picks the probable order class

month $\rightarrow M^2 \rightarrow s_2=7, c_2=7, r_2=7$ $P(z^{(2)}=A | x^{(2)}; \bar{\theta}^{(1)}) = \frac{.5^7 \cdot 3^1 \cdot 2^2}{.5^7 \cdot 3^1 \cdot 2^2 + .2^1 \cdot 3^1 \cdot 5^2} = .79$

$P(z^{(2)}=B | x^{(2)}; \bar{\theta}^{(1)}) = 1 - .79 = .01$

$z_{(1)}^{(2)} = A$

$M^3 \rightarrow s_3=1, c_3=2, r_3=7$ $P(z^{(3)}=A | x^{(3)}; \bar{\theta}^{(2)}) = \frac{.5^1 \cdot 3^2 \cdot 2^7}{.5^1 \cdot 3^2 \cdot 2^7 + .2^1 \cdot 3^2 \cdot 5^7} = .004$

$P(z^{(3)}=B | x^{(3)}; \bar{\theta}^{(2)}) = 1 - .004 = .996$ $z_{(1)}^{(3)} = B$

$M^4 \rightarrow s_4=8, c_4=1, r_4=1$ $P(z^{(4)}=A | x^{(4)}; \bar{\theta}^{(3)}) = \frac{.5^8 \cdot 3^1 \cdot 2^1}{.5^8 \cdot 3^1 \cdot 2^1 + .2^8 \cdot 3^1 \cdot 5^1} = .998$ $P(z^{(4)}=B | x^{(4)}; \bar{\theta}^{(3)}) = 1 - .998 = .002$

$M^5 \rightarrow s_5=3, c_5=3, r_5=4$ $P(z^{(5)}=A | x^{(5)}; \bar{\theta}^{(4)}) = \frac{.5^3 \cdot 3^3 \cdot 2^4}{.5^3 \cdot 3^3 \cdot 2^4 + .2^3 \cdot 3^3 \cdot 5^4} = .286$ $P(z^{(5)}=B | x^{(5)}; \bar{\theta}^{(4)}) = 1 - .286 = .714$

$M^5 \rightarrow s_6=5, c_6=2, r_6=5$ $P(z^{(6)}=A | x^{(6)}; \bar{\theta}^{(5)}) = \frac{.5^5 \cdot 3^2 \cdot 2^5}{.5^5 \cdot 3^2 \cdot 2^5 + .2^5 \cdot 3^2 \cdot 5^5} = .138$ $P(z^{(6)}=B | x^{(6)}; \bar{\theta}^{(5)}) = 1 - .138 = .862$

$z_{(1)}^{(6)} = B$

$z_{(1)} = [A, A, B, A, B, B]$ $\bar{\theta}^{(1)} = \frac{1}{30} [19, 4, 7, 7, 16]$

(R=)

1. Draw Ancestral Graph - only vars mentioned and all ancestors
2. Moralize by marrying the parents
3. Disorient \rightarrow directed with undirected
4. Delete the givars and their edges
5. 1) Vars disconnected \rightarrow independence - descendants given
2) not independent if connected parents

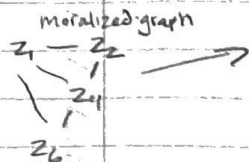
Bayes Net Assn: Each node (var)

Independent of its parents

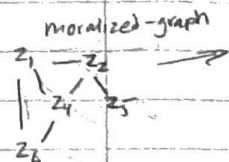
$$P(A, B, C) = P(A|C)P(B|C)$$

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

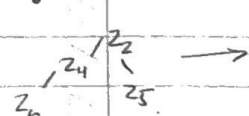
$$3 \text{ (a)} \exists x P(Z_1, Z_6 | Z_x) = P(Z_1 | Z_x) P(Z_6 | Z_x)?$$



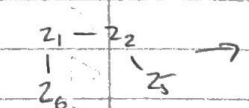
No, there exists no node that will make Z_1 and Z_6 conditionally independent because there is an edge that directly connects the two, so when you run D-separation they will still be connected and thus not conditionally ind.



No, Z_5 and Z_6 are not marginally independent because there exists a path from one to the other in the moralized graph.



$Z_5, Z_6 | Z_1$? **No**, not conditionally ind given Z_1 as even with Z_1 removed along with its connections from the graph, there is a path from Z_6 to Z_5 . All paths from Z_6 to Z_5 do not go through Z_1 .



$Z_5, Z_6 | Z_4$? **No**, not conditionally ind given Z_4 as even with Z_4 removed along with its connections from the graph, there is a path from Z_6 to Z_5 . All paths from Z_6 to Z_5 do not go through Z_4 .



Yes, Given both Z_4 and Z_1 , Z_5 and Z_6 are conditionally independent as there is no path btw them once conditioned vars and edges removed.

$$(b) P(Z_1, Z_2, Z_3, Z_4, Z_5, Z_6) = P(Z_1) P(Z_2 | Z_1) P(Z_3 | Z_1, Z_2) P(Z_4 | Z_1, Z_2) P(Z_5 | Z_2) P(Z_6 | Z_1, Z_4)$$

Π all vars given their parents why Bayes net Assn

$$(c) P(Z_1, Z_2, Z_3, Z_4, Z_5, Z_6) = P(Z_1) P(Z_2 | Z_1) P(Z_3 | Z_1) P(Z_4 | Z_1, Z_2) P(Z_5 | Z_2) P(Z_6 | Z_1, Z_4)$$

$$= n-1 + n(n-1) + n(n-1) + n(n-1) + n^2(n-1) + n^2(n-1)$$

$$= n-1 + 3n(n-1) + 2n^2(n-1) = n-1 + 3n^2 - 3n + 2n^3 - 2n^2 = \boxed{n^3 + 2n^2 - 2n - 1}$$

$$4) P(R=T | H=T) = \frac{P(R=T, H=T)}{P(H=T)} = \frac{\sum_{S,W,R} P(R=T, H=T, W, S)}{\sum_{S,W,R} P(H=T, S, W, R)} = \frac{.2781}{.6471} = .42976$$

↳ bottom page

$$\begin{aligned} P(R=T, H=T, W, S) &= \sum_S \sum_W P(S=S) P(R=T | S=S) P(W=W | S=S) P(H=T | R=T, W=W) \\ &= \sum_W \frac{1}{2} (P(R=T | S=T) P(W=W | S=T) P(H=T | R=T, W=W) + \\ &\quad \frac{1}{2} (P(R=T | S=F) P(W=W | S=F) P(H=T | R=T, W=W)) \\ &= \frac{1}{2} \frac{1}{10} P(W=F | S=T) P(H=T | R=T, W=F) + \frac{1}{2} \frac{1}{10} P(W=T | S=T) P(H=T | R=T, W=T) \\ &\quad + \frac{1}{2} \frac{1}{2} P(W=F | S=F) P(H=T | R=T, W=F) + \frac{1}{2} \frac{1}{2} P(W=T | S=F) P(H=T | R=T, W=T) \\ &= \frac{1}{2} \frac{1}{10} \frac{1}{5} \frac{9}{10} + \frac{1}{2} \frac{1}{10} \frac{4}{5} \frac{99}{100} + \frac{1}{2} \frac{1}{2} \frac{4}{5} \frac{9}{100} + \frac{1}{2} \frac{1}{2} \frac{4}{5} \frac{99}{100} = .2781 \quad \checkmark \text{ Numerator} \end{aligned}$$

$$\begin{aligned} P(H=T, S, W, R) &= \sum_S \sum_W \sum_R P(S=S) P(W=W | S=S) P(R=R | S=S) P(H=T | W=W, R=R) \\ &= \frac{1}{2} \left[\sum_W \sum_R P(W=W | S=T) P(R=R | S=T) P(H=T | W=W, R=R) + P(W=W | S=F) P(R=R | S=F) P(H=T | W=W, R=R) \right] \\ &= \frac{1}{2} \left[\sum_W P(W=W | S=T) P(R=T | S=T) P(H=T | W=W, R=T) + P(W=W | S=T) P(R=F | S=T) P(H=T | W=W, R=F) \right. \\ &\quad \left. + P(W=W | S=F) P(R=T | S=F) P(H=T | W=W, R=T) + P(W=W | S=F) P(R=F | S=F) P(H=T | W=W, R=F) \right] \\ &= \frac{1}{2} \left[P(W=T | S=T) P(R=T | S=T) P(H=T | W=T, R=T) + P(W=F | S=T) P(R=T | S=T) P(H=T | W=F, R=T) \right. \\ &\quad \left. + P(W=T | S=T) P(R=F | S=T) P(H=T | W=T, R=F) + P(W=F | S=T) P(R=F | S=T) P(H=T | W=F, R=F) \right. \\ &\quad \left. + P(W=T | S=F) P(R=T | S=F) P(H=T | W=T, R=T) + P(W=F | S=F) P(R=T | S=F) P(H=T | W=F, R=T) \right. \\ &\quad \left. + P(W=F | S=F) P(R=F | S=F) P(H=T | W=F, R=F) \right] \\ &= \frac{1}{2} \left[.8 \cdot .1 \cdot .99 + .2 \cdot .1 \cdot .9 + .8 \cdot .9 \cdot .99 + .2 \cdot .9 \cdot .9 + .2 \cdot .5 \cdot .99 + .8 \cdot .5 \cdot .9 + .2 \cdot .5 \cdot .9 + 0 \right] = .6471 \quad \checkmark \text{ Denominator} \end{aligned}$$