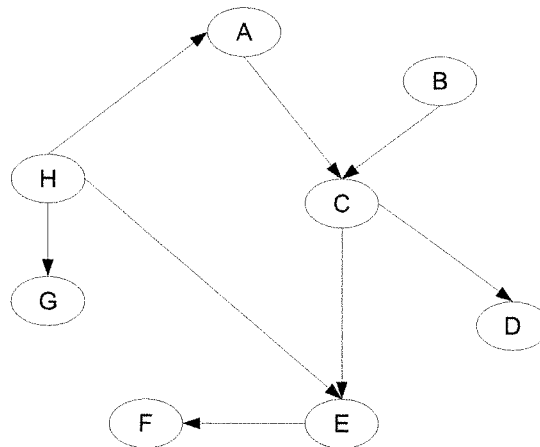


1. (6 points) Consider the following Bayesian network with variables A, B, C, D, E, F, G, H . Categorize the following as d -separated or d -connected with respect to the given BN.



(a) $A \perp\!\!\!\perp F \mid \{ \}$ or $A \perp\!\!\!\perp F$

(b) $H \perp\!\!\!\perp D \mid A$

(c) $H \perp\!\!\!\perp D \mid \{A, E\}$

(d) $B \perp\!\!\!\perp G \mid \{ \}$

(e) $B \perp\!\!\!\perp G \mid \{D\}$

(f) $A \perp\!\!\!\perp B \mid \{E, F\}$

(a) d -connected

(b) d -separated

(c) d -connected

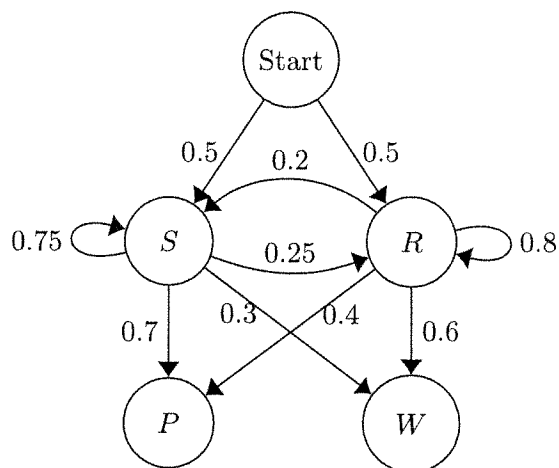
(d) d -separated

(e) d -connected

(f) d -connected

2. (13 points) Hidden Markov Models

Consider the following simple model of the weather in November using an HMM. There is a unobserved variable, X_t , indicating that the weather today can be either snowing (S) or raining (R), and you observe, E_t , what the majority of people are wearing: parkas (P) or wellington boots (W). This is modeled in the following HMM:



(a) (3 points) Compute $P(X_1 = S, X_2 = R, X_3 = R, X_4 = S)$

$$P(X_1 = S, X_2 = R, X_3 = R, X_4 = S) = 0.5 \times 0.25 \times 0.8 \times 0.2 = 0.02$$

(b) (4 points) Compute $P(X_1 = S | E_1 = P)$

$$P(X_1 = S | E_1 = P) = \frac{P(E_1 = P | X_1 = S) \cdot P(X_1 = S)}{P(E_1 = P)} = \frac{0.7 \times 0.5}{0.5 \times 0.7 + 0.5 \times 0.4} \approx 0.6364$$

(c) (6 points) Compute $P(E_1 = W, E_2 = W)$

$$P(E_1 = W) = 0.5 \times 0.3 + 0.5 \times 0.6 = 0.45$$

$$P(E_2 = W) = \sum_{x_1, x_2} P(E_2 = W | E_1 = W) T(x_1, x_2) P(E_1 = W | x_1)$$

$$\begin{aligned} &= 0.5 \times 0.75 \times 0.3 + 0.5 \times 0.25 \times 0.6 + 0.5 \times 0.8 \times 0.6 + 0.5 \times 0.2 \times 0.3 \\ &= 0.4575 \end{aligned}$$

$$P(E_1 = W, E_2 = W) = 0.45 \times 0.4575 = 0.205875$$

3. (19 points) Hidden Markov Models II

You are modelling the state of your health $\{h - \text{healthy}, c - \text{coming down with something}, \text{or } u - \text{unwell}\}$. Each day, you can observe whether you are sneezing s or not n to infer your state of health. Use the following information to model your health.

Initial Dist.		Transition Model			Emission Distribution		
State	$P(X_1)$	X_t	X_{t+1}	$P(X_{t+1} X_t)$	X_t	E_t	$P(E_t X_t)$
h	0.9	h	h	0.6	h	n	0.8
c	0.1	h	c	0.2	c	n	0.3
u	0.0	h	u	0.2	u	n	0.5
		c	h	0.3	h	s	0.2
		c	c	0.2	c	s	0.7
		c	u	0.5	u	s	0.5
		u	h	0.7			
		u	c	0.2			
		u	u	0.1			

(a) (2 points) What is $P(X_1 = h, X_2 = c, X_3 = u)$?

$$0.9 \times 0.2 \times 0.5 = 0.09$$

(b) (2 points) What is $P(X_1 = u, X_2 = c, X_3 = h)$?

$$0$$

(c) (4 points) On the first day, you did not sneeze, $E_1 = n$. What is the probability you are coming down with something given this observation?

$$P(X_1 = c | E_1 = n) = \frac{P(E_1 = n | X_1 = c) P(X_1 = c)}{P(E_1 = n)}$$

$$\begin{aligned}
 P(E_1 = n) &= \sum_{X_1} P(X_1 = c | E_1 = n) P(X_1) \\
 &= 0.8 \times 0.9 + 0.3 \times 0.1 + 0.5 \times 0 \\
 &= 0.75
 \end{aligned}$$

$$P(X_1 = c | E_1 = n) = \frac{0.3 \times 0.1}{0.75} = 0.04$$

- (d) (8 points) You observe not sneezing on day 1 and sneezing on day 2. What's the probability of coming down with something given the sequence of observations?

$$P(E_1=n | X_1=h) = 0.8 \times 0.9 = 0.72$$

$$P(E_1=n | X_1=c) = 0.3 \times 0.1 = 0.03$$

$$P(E_1=n | X_1=u) = 0$$

$$\begin{aligned} P(E_2=s, E_1=n | X_2) &= \sum_{X_1, X_2} P(E_2=s | X_2) \cdot P(X_2 | X_1) \cdot P(E_1=n | X_1) \\ &= 0.2 \times [(0.6 \times 0.9 \times 0.8) + (0.1 \times 0.3 \times 0.3) + 0] + 0.7 \times [(0.9 \times 0.8 \times 0.2) + (0.1 \times 0.3 \times 0.2) + 0] \\ &\quad + 0.5 \times [(0.9 \times 0.8 \times 0.2) + (0.1 \times 0.3 \times 0.5) + 0] = 0.0882 + 0.105 + 0.0795 = 0.2727 \end{aligned}$$

$$P(E_2=s, E_1=n | X_2=c) = 0.7 \times [(0.9 \times 0.8 \times 0.2) + (0.1 \times 0.3 \times 0.2) + 0] = 0.105$$

$$P(X_2=c | E_1=n, E_2=s) = \frac{0.105}{0.2727} \approx 0.385$$

- (e) (3 points) You can confirm that you were healthy on days one and two. What is the probability that you will be unwell on day 3?

$$P(X_3=u | X_2=h) = P(X_{t+1}=u | X_t=h) = 0.2$$

4. (12 points) Markov Decision Process

A student selects fruit from a bowl of *Apples* - A and *Oranges* - O . At each state she has either an *Apple* or *Orange* in her hand. There is only one action, *Swap* - S , when she returns the fruit in her hand to the bowl, and selects a new piece of fruit, where $P(A) = 0.7$. The MDP has the following information:

States: A - apple, O - orange

Actions: S - swap

Start state: A - apple

there are no terminal states

Let $R(A, S, O) = 3$ and $R(O, S, A) = 2$, with all other rewards = 0. Assume $\gamma = 0.5$

- (a) (12 points) Run value iteration for this MDP for three iterations and fill in the value estimates in the table. Show your work.

i	$V_i^*(A)$	$V_i^*(O)$
0	0	0
1	0.9	1.4
2	1.425	1.925
3	1.6875	2.1875

(b) (3 points (bonus)) What are $V^*(A)$ and $V^*(O)$? Hint: solve the Bellman equations

$V^*(A)$ and $V^*(O)$ means converge, so $V_k(A) = V_{k+1}(A)$, $V_k(O) = V_{k+1}(O)$

$$\text{Then: } V_{k+1}(A) = T(A, s, A) [R(A, s, A) + \gamma V_k(A)] + T(A, s, O) [R(A, s, O) + \gamma V_k(O)] \quad (1)$$

$$V_{k+1}(O) = T(O, s, A) [R(O, s, A) + \gamma V_k(A)] + T(O, s, O) [R(O, s, O) + \gamma V_k(O)] \quad (2)$$

$$\therefore V_{k+1}(A) = V_k(A), \quad V_{k+1}(O) = V_k(O)$$

$$\therefore (1) \Rightarrow V_k(A) = 0.7[0 + 0.5 V_k(A)] + 0.3[3 + 0.5 V_k(O)]$$

$$(2) \Rightarrow V_k(O) = 0.7[2 + 0.5 V_k(A)] + 0.3[0 + 0.5 V_k(O)]$$

$$\text{from (1)} \Rightarrow \cancel{V_k(O) = 2 + V_k(A) - 0.3} \quad (3) \quad V_k(O) = \frac{0.65 V_k(A) - 0.9}{0.15}$$

$$\text{plug (3) into (2)} \Rightarrow 0.85 \times \frac{0.65 V_k(A) - 0.9}{0.15} = 1.4 + 0.35 V_k(A)$$

$$\Rightarrow V_k(A) = 1.95 \quad (4)$$

$$\text{plug (4) into (3)} \quad V_k(O) = 2.45$$

The answer is $V^*(A) = 1.95$ $V^*(O) = 2.45$