

Homework VII

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Q.1 A graph with no links is a trivial D-Map.
True.

A graph is said to be D-Map of a distribution if all CI satisfied by distribution is reflected on the graph, of course graph with no links will reflect any conditional independency.

Q.2.

- a- A conditionally independent of D give $\{B, C\}$ - True.
- b- E marginally independent of F - No
- c- Delete edges to make A independent of C.
 $A \rightarrow C$

Q.3.

Tables for $p(a)$, $p(c|a)$, $p(b|c)$ by marginalizing and conditioning the joint distribution from the given table :-

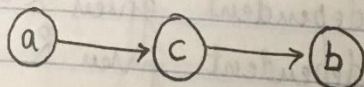
a	$p(a)$
0	0.6
1	0.4

a	c	$p(c a)$
0	0	0.4
0	1	0.6
1	0	0.6
1	1	0.4

c	b	$p(b c)$
0	0	0.8
0	1	0.2
1	0	0.4
1	1	0.6

Multiplying the three distribution together we recover the joint distribution $p(a, b, c)$ given in the table, thereby allowing us to verify the validity of the decomposition $p(a, b, c) = p(a) * p(c|a) * p(b|c)$.

We can express the distribution using the graph.



8.4 Given graphical model with 4 binary variables

$$\begin{aligned}
 \text{a) } P(S=1|V=1) & \text{ is } \frac{P(S=1, V=1)}{P(V=1)} \\
 &= \frac{1}{P(V=1)} \sum_{R=0}^1 \sum_{G=0}^1 P(V=1) * P(G) * P(R|V=1, G) * P(S=1|G) \\
 &= \sum_{R, G} P(G) * P(R|V=1, G) * P(S=1|G) \\
 &= \sum_G P(G) * P(S=1|G) \sum_R P(R|V=1, G) \\
 &= \sum_G P(G) * P(S=1|G) * 1 \\
 &= P(G=0) * P(S=1|G=0) + P(G=1) * P(S=1|G=1) \\
 &= \alpha(1-\gamma) + (1-\alpha) * (1-\beta) \\
 &= \alpha - \alpha\gamma + 1 + \alpha\beta - \alpha - \beta \\
 &= 1 - \alpha\gamma + \alpha\beta - \beta
 \end{aligned}$$

b. $P(S=1|V=1)$ and $P(S=1|V=0)$ are same because they are independent of V .

c. MLE can be estimated by counting events. Thus, $\alpha = \frac{1}{3}$
 $\beta = 0$ and $\gamma = 1$.

V and S are independent given nothing

V and S are independent given G

V and S are independent given R & G

V and S are dependent given R .

Q.5

a.

The CPDs for nodes 1, 2, 3 have 1 free parameters each (since they are Bernoulli). $p(H|X_{1:3})$ has 8 parameters one per conditioning case.

$p(X_i|H)$ for $i=4:6$ are 2×2 tables, but due to the sum of one constraint, only have 2 free parameters.

So total of $3 \times 1 + 8 + 3 \times 2 = 17$.

b.

For the graph on the right, the CPDs for nodes 1, 2, 3 have 1 free parameters each (since they are Bernoulli).

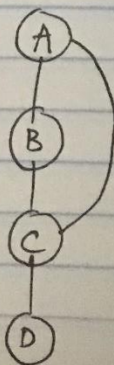
$p(X_4|X_{1:3})$ has 8 parameters, one per conditioning case. $p(X_5|X_{1:4})$ has 16 parameters.

$p(X_6|X_{1:5})$ has 32 parameters.

In total, $3 + 8 + 16 + 32 = 59$ parameters.

Q.6.

The functions after instantiating evidence variable are $P(B|A)$, $P(C|A, B)$, $P(D|C)$ and function of D . The induced graph along the ordering ABCD is shown below. The no of children for A, B, C & D are 2, 1, 1 and 0 resp, so the width of the tree is 2. The complexity of the variable elimination algorithm is $O(n \exp(w+1))$, where n is no. of non-evidence variables and w is the width of the ordering. Therefore the complexity is $O(4 \exp(3))$.



Q.7 The functions after instantiating evidence variables are $P(B|A)$, $P(C|B)$, $P(D|C)$, $P(A)$ and function of D .

The induced graph along the ordering BCDA is shown below.

The number of children for B, C, D and A are 2, 2, 1 and 0 respectively. so the tree-width is 2. The complexity of the variable elimination algorithm is $O(n \exp(w+1))$, where n is no. of non-evidence variables and w is the width of the ordering. Thus, the complexity is $O(4 \exp(3))$.

