# ADVANCED MACHINE LEARNING EXERCISE #1 SOLUTION

Uri Avron [uriavron@gmail.com] [308046994] Jonathan Somer [jonathan.somer@gmail.com] [307923383] Matan Harel [matan.harel.mh@gmail.com] [302695721]

March 22, 2018

(a) Due to simmetry, for any pair i, j it holds that  $q(x_i, x_j) = \frac{1}{6} + \frac{1}{12} = \frac{1}{4}$  and for any  $k \in [3]$   $q(x_k) = \frac{1}{2}$ . Therefore  $q(x_i, x_j) = q(x_i)q(x_j)$  which implies  $X_i \perp X_j \in I(q)$ . Moreover, it is now clear that for any permutation (i, j, k) of [3] it holds that

$$\begin{split} q(x_i|x_k)q(x_j|x_k) &= \frac{1}{4} \\ &\neq \begin{cases} \frac{1}{6} & x_1 \oplus x_2 \oplus x_3 = 0 \\ \frac{1}{3} & x_1 \oplus x_2 \oplus x_3 = 1 \end{cases} = 2q(x_1, x_2, x_3) = q(x_i, x_j|x_k) \end{split}$$

which implies  $X_i \perp X_j | X_k \notin I(q)$ , and

$$q(x_i) = \frac{1}{2}$$

$$\neq \begin{cases} \frac{1}{3} & x_1 \oplus x_2 \oplus x_3 = 0\\ \frac{2}{3} & x_1 \oplus x_2 \oplus x_3 = 1 \end{cases} = 4q(x_1, x_2, x_3) = q(x_i | x_j, x_k)$$

which implies  $X_i \perp X_j, X_k \notin I(q)$ . so overall we get  $I(q) = \{X_1 \perp X_2, X_2 \perp X_3, X_3 \perp X_1\}$ .

- (b) No, proof by contradiction. Let us assume there exists a DAG G where  $I_{LM}(G) = I(q)$ , so  $X_i \perp X_j \in I_{LM}(G)$  which means  $Pa(i) = \emptyset$  and  $ND(i) = \{X_j\}$  but this is true for any  $i, j \in \{(1, 2), (2, 3), (3, 1)\}$  and hence the contradiction is obvious (there are no parents but every node has one decendant for example).  $\square$
- (c) No, proof by contradiction. Let us assume there exists an undirected graph G where  $I_{sep}(G) = I(q)$ , so  $X_i \perp X_j \in I_{sep}(G)$  which means there are no edges in G but in this case for example  $X_1 \perp X_2, X_3 \in I_{sep}(G)$  where  $X_1 \perp X_2, X_3 \notin I_{sep}(G)$  and hence  $I_{sep}(G) \neq I(q)$ , a contradiction.  $\square$

From  $X \perp Y|Z,W$ , we have p(x|y,z,w) = p(x|z,w). From  $X \perp W|Z,Y$ , we have p(x|y,z,w) = p(x|w,z,y) = p(x|z,y). By combining the equations we get p(x|w,z) = p(x|y,z). We now inspect each side:

$$\begin{split} p(x|w,z) &= \frac{p(x,w,z)}{p(w,z)} = \frac{p(x,w|z)p(z)}{p(w|z)p(z)} = \frac{p(x,w|z)}{p(w|z)} \\ p(x|y,z) &= \frac{p(x,y,z)}{p(y,z)} = \frac{p(x,y|z)p(z)}{p(y|z)p(z)} = \frac{p(x,y|z)}{p(y|z)} \end{split}$$

Hence we get p(x,w|z)p(y|z)=p(x,y|z)p(w|z). Now, by summing each side by w we get p(x|z)p(y|z)=p(x,y|z) and therefore  $X\perp Y|Z$ . Now, from  $X\perp W|Z,Y$  we also have p(x,w|y,z)=p(x|y,z)p(w|y,z). Again, we inspect each side:

$$p(x, w|y, z) = \frac{p(x, w, y, z)}{p(y, z)} = \frac{p(x, w, y|z)p(z)}{p(y, z)}$$

$$p(w|y, z) = \frac{p(w, y, z)}{p(y, z)} = \frac{p(y, w|z)p(z)}{p(y, z)}$$

$$\Rightarrow \frac{p(x, w, y|z)p(z)}{p(y, z)} = p(x|y, z)\frac{p(y, w|z)p(z)}{p(y, z)}$$

$$\Rightarrow p(x, w, y|z) = p(y, w|z)p(x|y, z)$$

From  $X \perp Y|Z$  we have p(x|y,z) = p(x|z) and by putting it in the last equation we get p(x,w,y|z) = p(y,w|z)p(x|z) and by definition  $X \perp Y, W|Z$ .  $\square$ 

We define  $S = Pa(i) \cup Ch(i) \cup \bigcup_{j \in Ch(i)} Pa(j)$  and argue that S is the Markov

Blanket for some Bayesian network p on G. We first show that  $X_i \perp X_{\bar{S}\setminus i}|X_S \in I_{d-sep}(G)$ . Let  $k \in X_{\bar{S}\setminus i}$ . We have 3 cases:

- If there is an undirected path between i and j via  $k \in Ch(i)$  and  $l \in Pa(j)$ , then  $l \in S$  is not the child in this v-structure.
- If there is an undirected path between i and j via  $k \in Ch(i)$  but not via Pa(j), then  $k \in S$  and k is not in a v-stracture in the path.
- If there is an undirected path between i and j via  $k \in Pa(i)$ , then  $k \in S$  is not in a v-structure.

Overall, there is no active trail between  $X_i$  and  $X_{\bar{S}\setminus i}$  given  $X_S$  and we get  $X_i \perp X_{\bar{S}\setminus i}|X_S \in I_{d-sep}(G) \subseteq I(p)$  by definition and Proposition 2.3.1. We now have left to show the minimalism of S. If we remove  $k \in Pa(i) \cup Ch(i)$ , it is clear that  $X_i$  and  $X_k$  are dependent given  $X_S$  and hence  $X_i \perp X_{\bar{S}\setminus i}|X_S \notin I(p)$ . If we remove  $k \in \bigcup_{j \in Ch(i)} Pa(j)$ , we have an active trail i and k given  $X_S$  (via

the mutual child) and hence  $X_i \perp X_{\bar{S}\backslash i}|X_S \notin I_{d-sep}(G)$ . We know that except for measure zero set, all Baseyian networks on G will hold  $I(p) = I_{d-sep}(G)$ , and therefore in any case of removal we get  $X_i \perp X_{\bar{S}\backslash i}|X_S \notin I(p)$  so S is indeed minimal.  $\square$ 

# Question 4

- (a) By Theorem 4, it's suffices to show that  $I_{pair}(G) \subseteq I(p)$ . Indeed, if  $X_i \perp X_j | X_{V \setminus \{i,j\}} \in I_{pair}(G)$  then by definition of G we get  $ij \notin E$  and hence  $X_i \perp X_j | X_{V \setminus \{i,j\}} \in I(p)$  since otherwise edge ij was supposed to be added to G. Therefore  $I_{sep}(G) \subseteq I(p)$ .  $\square$
- (b) Towards contradiction, let us assume that G is not a minimal I-map for p. Therefore, there exists edge ij such that it can be removed and still  $I_{sep}(G) \subseteq I(p)$ . On one hand, be the definition of G, we have  $X_i \perp X_j | X_{V \setminus \{i,j\}} \notin I(p)$ . On the other hand, since now  $ij \notin E$ , we get  $X_i \perp X_j | X_{V \setminus \{i,j\}} \in I_{pair}(G)$ , and hence  $X_i \perp X_j | X_{V \setminus \{i,j\}} \in I_{sep}(G)$  so therefore  $I_{sep}(G) \nsubseteq I(p)$ , a contradiction. We thus conclude G is indeed minimal I-map for p.  $\square$

Obviously,  $I_{sep}(G) = \{X_1 \perp X_3 | X_{2,4}, X_2 \perp X_4 | X_{1,3}\}$ . First, we show that  $X_1 \perp X_3 | X_{2,4} \in I(p)$ . Because  $p(x_3 = 0) = 1/2$ , the following tables show  $p(x_1 | x_{2,3,4}) = p(x_1 | x_{2,4})$  and hence  $X_1 \perp X_3 | X_{2,4} \in I(p)$ :

Each cell is the probability of  $p(x_1|x_{2,3,4})$ :

$x_1 x_{2,3,4}$	0,0,0	1,0,0	0,1,0	1,1,0	0,0,1	1,0,1	0,1,1	1,1,1
0	1/2	0	undefined	0	1	unedfined	1	1/2
1	1/2	1	undefined	1	0	undefined	0	1/2

Each cell is the probability of  $p(x_1|x_{2,4})$ :

$x_1 x_{2,4}$	0,0	1,0	0,1	1,1
0	1/2	0	1	1/2
1	1/2	1	0	1/2

 $X_2 \perp X_4 | X_{1,3} \in I(p)$  is showed in the same way. Therefore we have  $I_{sep}(G) \subseteq I(p)$ . To end our proof, we now show that p is not a Markov network with respect to G. Towards a contradiction, let us assume that p is indeed a Markov network with respect to G. We know that  $\mathcal{C}(G) = \{\{X_1, X_4\}, \{X_1, X_2\}, \{X_3, X_4\}, \{X_2, X_3\}\}$ . Hence, by the definition of Markov network,  $p(\mathbf{x})$  can be written as:

$$p(\mathbf{x}) = Z^{-1} \prod_{c \in \mathcal{C}(G)} \phi_c(x_c) = Z^{-1} \phi_{12}(x_{1,2}) \phi_{23}(x_{2,3}) \phi_{34}(x_{3,4}) \phi_{41}(x_{4,1})$$

Let us inspect the following equations:

$$p(0,0,0,0) = \phi_{12}(0,0)\phi_{23}(0,0)\phi_{34}(0,0)\phi_{41}(0,0) = Z/8 \tag{1}$$

$$p(0,0,1,1) = \phi_{12}(0,0)\phi_{23}(0,1)\phi_{34}(1,1)\phi_{41}(1,0) = Z/8 \tag{2}$$

$$p(1,1,1,0) = \phi_{12}(1,1)\phi_{23}(1,1)\phi_{34}(1,0)\phi_{41}(0,1) = Z/8$$
 (3)

$$p(0,0,1,0) = \phi_{12}(0,0)\phi_{23}(0,1)\phi_{34}(1,0)\phi_{41}(0,0) = 0 \tag{4}$$

From (4), we know that  $\phi_{12}(0,0)=0 \lor \phi_{23}(0,1)=0 \lor \phi_{34}(1,0)=0 \lor \phi_{41}(0,0)=0$ , but if any one of those is true, at least one out of (1), (2), (3) will be equal to  $0 \ne Z/8$ , a contradiction. We therefore conclude that p is not a Markov network with respect to G.  $\square$ 

First, w.l.o.g we assume that  $\forall ij \in E, i < j$ . Proof by induction on the size of V. For |V| = 1 the claim holds trivially. Let us assume the claim holds  $\forall k \in [n-1]$  and we now prove for n. We know that:

$$p(x_{[n]}) = p(x_n | x_{[n-1]}) p(x_{[n-1]})$$
(5)

From the inductive hypothesis:

$$p(x_{[n-1]}) = \prod_{i=1}^{n-1} p(x_i) \prod_{\substack{ij \in E \\ i,j \in [n-1]}} \frac{p(x_i, x_j)}{p(x_i)p(x_j)}$$
(6)

By Theorem 4.1 (if p factorizes according to G the  $I_{sep}(G) \subseteq I(p)$ ) and the fact that  $I_{LM}(G) \subseteq I_{sep}(G)$ :

$$p(x_n|x_{[n-1]}) = p(x_n|x_{Nbr(n)}) = \frac{p(x_n, x_{Nbr(n)})}{p(x_{Nbr(n)})}$$

G is a tree a graph, hence there are no circles and therefore, w.l.o.g Nbr(n) < n-1. So, again by the inductive hypothesis:

$$p(x_{n}, x_{Nbr(n)}) = \prod_{i \in Nbr(n) \cup \{n\}} p(x_{i}) \prod_{\substack{ij \in E \\ i,j \in Nbr(n) \cup \{n\}}} \frac{p(x_{i}, x_{j})}{p(x_{i})p(x_{j})}$$

$$p(x_{Nbr(n)}) = \prod_{i \in Nbr(n)} p(x_{i}) \prod_{\substack{ij \in E \\ i,j \in Nbr(n)}} \frac{p(x_{i}, x_{j})}{p(x_{i})p(x_{j})}$$

$$\Rightarrow p(x_{n}|x_{[n-1]}) = p(x_{n}) \prod_{in \in E} \frac{p(x_{i}, x_{j})}{p(x_{i})p(x_{j})}$$
(7)

By (5), (6), (7) we get:

$$p(x_n) = \prod_{i=1}^{n} p(x_i) \prod_{ij \in E} \frac{p(x_i, x_j)}{p(x_i)p(x_j)}$$