

Assignment2

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Problem 1

Given the local Markov property for UGs,

$$X_i \perp\!\!\!\perp X \setminus Cl(X_i, \mathcal{G}) | Ne(X_i, \mathcal{G}) \text{ and } X_i \sim X_j$$

$$\Rightarrow X_i \perp\!\!\!\perp X_j \cup (X \setminus Cl(X_i, \mathcal{G}) \cup X_j) | Ne(X_i, \mathcal{G})$$

$$\Rightarrow X_i \perp\!\!\!\perp X_j | Ne(X_i, \mathcal{G}) \cup (X \setminus Cl(X_i, \mathcal{G}) \cup X_j) \text{ (by weak union)}$$

$$\Rightarrow X_i \perp\!\!\!\perp X_j | Ne(X_i, \mathcal{G}) \cup (X \setminus Ne(X_i, \mathcal{G}) \cup X_i \cup X_j)$$

$$\Rightarrow X_i \perp\!\!\!\perp X_j | X \setminus (X_i \cup X_j) \Rightarrow X_i \perp\!\!\!\perp X_j | X \setminus \{X_i, X_j\}$$

This is the pairwise Markov property. Therefore, we can conclude that local Markov property \Rightarrow pairwise Markov property in undirected graph \mathcal{G} .

Problem 2

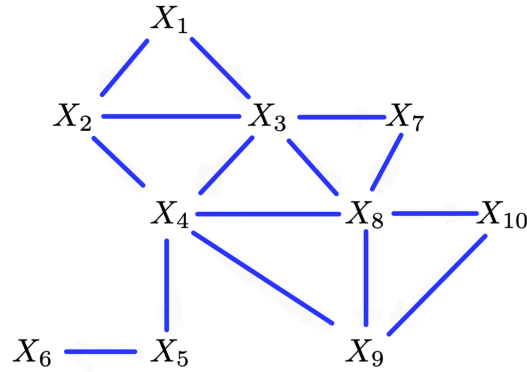


Figure 1: Moralized graph

- (a) When factorizing by maximal clique, the joint distribution can be written as:

$$p(x) = \frac{1}{Z} \phi_{123}(x_1, x_2, x_3) \phi_{234}(x_2, x_3, x_4) \phi_{378}(x_3, x_7, x_8) \phi_{348}(x_3, x_4, x_8) \phi_{489}(x_4, x_8, x_9) \phi_{234}(x_8, x_9, x_{10}) \phi_{45}(x_4, x_5) \phi_{56}(x_5, x_6)$$

There are 8 factor potentials.

- (b) When the scope has 3 variables, there are 3 parameters for each variable, 3 parameters for pairs, and 1 parameter for three-way interaction. When the scope has two variables, there are 2 parameters for

single variable and 1 parameters for pairs. From (a), we have 6 scopes with 3 variables and 2 scopes with 2 variables. Therefore, there are $(3 + 3 + 1) \times 6 + (2 + 1) \times 2 = 48$ variables in total.

- (c) There are 10 variables and each can take on either 0 or 1, so there are $2^{10} = 1024$ possible combinations. The joint distribution must sum to 1, and the last one will be determined automatically when all the other 9 variable are set. So $2^{10} - 1 = 1023$ parameters would be required.

- (d) Factorization property in DAG \mathcal{G} :

$$p(x_1, x_2, \dots, x_{10}) = \prod_{i=1}^{10} p(x_i | Pa(X_i, \mathcal{G}))$$

$$= p(x_1) p(x_2 | x_1) p(x_3 | x_1) p(x_4 | x_2, x_3) p(x_5 | x_4) p(x_6 | x_5) p(x_7 | x_3) p(x_8 | x_3, x_7) p(x_9 | x_4, x_8, x_{10}) p(x_{10} | x_8)$$

When $x_i = 1$, the probability can be written as $p(x_i = 1 | Pa(X_i, \mathcal{G}))$. The probability where $x_i = 0$ can be obtained by $1 - p(x_i = 1 | Pa(X_i, \mathcal{G}))$ so we can focus on the combination of the parents. By the above factorization formula, the required number of parameters are $2^0 + 2^1 + 2^1 + 2^2 + 2^1 + 2^1 + 2^1 + 2^2 + 2^3 + 2^1 = 29$.

Problem 3

Independencies of \mathcal{G}_1 :

$$A \perp_d B | \phi, B \perp_d D | \phi, D \perp_d C | \phi, C \perp_d A | \phi, A \perp_d D | \phi, B \perp_d C | \phi$$

Independencies of \mathcal{G}_2 :

$$A \perp\!\!\!\perp B | \{E, C, D\}, B \perp\!\!\!\perp D | \{E, A, C\}, D \perp\!\!\!\perp C | \{E, A, B\}, C \perp\!\!\!\perp A | \{E, D, B\}, A \perp\!\!\!\perp D | \{E, B, C\}, B \perp\!\!\!\perp C | \{E, A, D\}$$

Independencies of \mathcal{G}_3 :

$$A \perp_d B | E, B \perp_d D | E, D \perp_d C | E, C \perp_d A | E, A \perp_d D | E, B \perp_d C | E$$

Both BN and MRF models infer conditional independencies based on the absence of edges. In a BN, non-adjacent variables require some set S (possibly empty) to make them independent, whereas in an MRF, non-adjacent variables are independent when conditioned on all remaining variables.

Adding adjacency between A and B changes the independencies as follows.

Independencies of \mathcal{G}_1 :

$$A \text{ and } B \text{ are no longer independent, } B \perp_d D | \phi \text{ or } B \perp_d D | A, D \perp_d C | \phi \text{ or } D \perp_d C | \{A, B\},$$

$$C \perp_d A | \phi \text{ or } C \perp_d A | B, A \perp_d D | \phi \text{ or } A \perp_d D | B, B \perp_d C | \phi \text{ or } B \perp_d C | A$$

Independencies of \mathcal{G}_2 :

A and B are no longer independent. Aside from that, all the independencies remain the same.

Independencies of \mathcal{G}_3 :

A and B are no longer independent.

- When $B \rightarrow A$ is added, A becomes a collider so all the independencies remain the same except A and B .

- When $B \leftarrow A$ is added:

$$B \perp_d D | \{E, A\}, D \perp_d C | \{E, A\}, C \perp_d A | \{E, A\}, A \perp_d D | \{E, A\}, B \perp_d C | \{E, A\}$$

Problem 4

Proof of $\mathbf{A} \perp_d \mathbf{B} | \mathbf{C}$ in DAG $\mathcal{G} \Rightarrow \mathbf{A} \perp\!\!\!\perp \mathbf{B} | \mathbf{C}$ in $(\mathcal{G}_{An(\mathbf{A}, \mathbf{B}, \mathbf{C})})^m$:

When $\mathbf{A} \perp_d \mathbf{B} | \mathbf{C}$ in DAG \mathcal{G} , all the paths from \mathbf{A} to \mathbf{B} through \mathbf{C} should be blocked. Noncollider in \mathbf{C} makes the path non-active and collider in \mathbf{C} makes the path active given \mathbf{C} is in the conditioning set. If

there are more than one node between \mathbf{A} and \mathbf{B} , the path will be non-active because we cannot have nodes in \mathbf{C} between \mathbf{A} and \mathbf{B} to be all colliders. In other words, \mathbf{A} and \mathbf{B} are d-connected only when there is a node in \mathbf{C} that is a child of both \mathbf{A} and \mathbf{B} , which means there is no node c in \mathbf{C} such that $A \rightarrow c \leftarrow B$ under $\mathbf{A} \perp_d \mathbf{B} | \mathbf{C}$. Additionally, there is no direct path between \mathbf{A} and \mathbf{B} in DAG \mathcal{G} . Thus, when constructing $(\mathcal{G}_{An(\mathbf{A}, \mathbf{B}, \mathbf{C})})^m$, the non-adjacency of \mathbf{A} and \mathbf{B} is maintained. Therefore, $\mathbf{A} \perp\!\!\!\perp \mathbf{B} | \mathbf{C}$ in $(\mathcal{G}_{An(\mathbf{A}, \mathbf{B}, \mathbf{C})})^m$ holds.

Proof of $\neg(\mathbf{A} \perp_d \mathbf{B} | \mathbf{C} \text{ in DAG } \mathcal{G}) \Rightarrow \neg(\mathbf{A} \perp\!\!\!\perp \mathbf{B} | \mathbf{C} \text{ in } (\mathcal{G}_{An(\mathbf{A}, \mathbf{B}, \mathbf{C})})^m)$:

When \mathbf{A} and \mathbf{B} are not d-separated given \mathbf{C} , at least one path from \mathbf{A} to \mathbf{B} has to be active. As mentioned above, this is true only when there is no node c in \mathbf{C} such that $A \rightarrow c \leftarrow B$ under $\mathbf{A} \perp_d \mathbf{B} | \mathbf{C}$. The moralization of DAG \mathcal{G} will create a new edge between \mathbf{A} and \mathbf{B} , so they will no longer be independent given \mathbf{C} in $\mathbf{A} \perp\!\!\!\perp \mathbf{B} | \mathbf{C}$ in $(\mathcal{G}_{An(\mathbf{A}, \mathbf{B}, \mathbf{C})})^m$.

Therefore, $\mathbf{A} \perp_d \mathbf{B} | \mathbf{C}$ in DAG \mathcal{G} if and only if $\mathbf{A} \perp\!\!\!\perp \mathbf{B} | \mathbf{C}$ in $(\mathcal{G}_{An(\mathbf{A}, \mathbf{B}, \mathbf{C})})^m$.