Assignment2

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Problem 1

Given the local Markov property for UGs,
$X_i \perp\!\!\!\perp X\backslash Cl(X_i, \mathcal{G}) | Ne(X_i, \mathcal{G})$ and $X_i \nsim X_j$
$\Rightarrow X_i \perp\!\!\!\perp X_j \cup (X\backslash Cl(X_i, \mathcal{G}) \cup X_j) | Ne(X_i, \mathcal{G})$
$\Rightarrow X_i \perp\!\!\!\perp X_j | Ne(X_i, \mathcal{G}) \cup (X\backslash Cl(X_i, \mathcal{G}) \cup X_j)$ (by weak union)
$\Rightarrow X_i \perp\!\!\!\perp X_j | Ne(X_i, \mathcal{G}) \cup (X\backslash Ne(X_i, \mathcal{G}) \cup X_i \cup X_j)$
$\Rightarrow X_i \perp\!\!\!\perp X_j | X\backslash(X_i \cup X_j) \Rightarrow X_i \perp\!\!\!\perp X_j | X\backslash\{X_i, X_j\}$
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

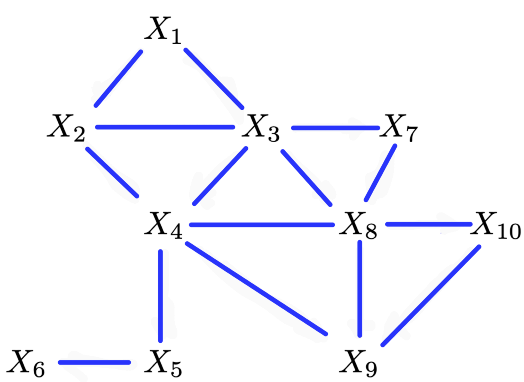

Figure 1: Moralized graph

(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 $\mathcal{G}$:
$p(x_1, x_2, ..., x_{10}) = \prod_{i=1}^{10} p(x_i \mid Pa(X_i, \mathcal{G}))$
$=p(x_1)p(x_2|x_1)p(x_3|x_1)p(x_4|x_2,x_3)p(x_5|x_4)p(x_6|x_5)p(x_7|x_3)p(x_8|x_3,x_7)p(x_9|x_4,x_8,x_{10})p(x_{10}|x_8)$
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 and B are no longer independent, $B \perp_d D|\phi$ or $B \perp_d D|A$, $D \perp_d C|\phi$ or $D \perp_d C|\{A,B\}$,
$C \perp_d A|\phi$ or $C \perp_d A|B$, $A \perp_d D|\phi$ or $A \perp_d D|B$, $B \perp_d C|\phi$ 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 $B \to A$ 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 $\mathbf{B}$. So, 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 $\neg(\mathbf{A} \perp_d \mathbf{B}|\mathbf{C}$ in DAG $\mathcal{G}) \Rightarrow \neg(\mathbf{A} \perp\!\!\!\perp \mathbf{B}|\mathbf{C}$ 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 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 $(\mathcal{G}_{An(\mathbf{A},\mathbf{B},\mathbf{C})})^m$.