Q1-1: You are presented with a dataset that has hidden/missing variables that influences your data. You are asked to use Expectation Maximization algorithm to best capture the data.
How would you define the **E** and **M** in Expectation Maximization?

1. Estimate the Missing/Latent Variables in the Dataset, Maximize the likelihood over the parameters in the model
2. Estimate the number of Missing/Latent Variables in the Dataset, Maximize the likelihood over the parameters in the model
3. Estimate likelihood over the parameters in the model, Maximize the number of Missing/Latent Variables in the Dataset
4. Estimate the likelihood over the parameters in the model, Maximize the number of parameters in the model

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4. Estimate the likelihood over the parameters in the model, Maximize the number of parameters in the model

Q1-2: Select the correct statement.

A. The EM algorithm is guaranteed to converge but may not reach a global optimum.

B. The objective function optimized by the EM algorithm can also be optimized by a gradient descent algorithm which will find the global optimal solution, whereas EM finds its solution more quickly but may return only a locally optimal solution.

1. Both the statements are TRUE.
2. Statement A is TRUE, but statement B is FALSE.
3. Statement A is FALSE, but statement B is TRUE.
4. Both the statements are FALSE.

Q1-2: Select the correct statement.

A. *The EM algorithm is guaranteed to converge but may not reach a global optimum.*
B. *The objective function optimized by the EM algorithm can also be optimized by a gradient descent algorithm which will find the global optimal solution, whereas EM finds its solution more quickly but may return only a locally optimal solution.*

1. Both the statements are TRUE.
2. Statement A is TRUE, but statement B is FALSE. ⬅
3. Statement A is FALSE, but statement B is TRUE.
4. Both the statements are FALSE.

For the second statement:
The only false part is that the gradient descent algorithm will find the global optimal solution. Gradient descent can also get stuck in a local optima.

Q2-1: Select the correct statement.

A. *The Chow-Liu algorithm not necessarily always choose edges from a complete graph.*
B. *The algorithm tries to find a minimum spanning tree of a graph to minimize the negative log-likelihood of training data.*
C. *Edge directions can be assigned randomly in the Chow-Liu algorithm.*

1. True, True, True
2. False, False, True
3. True, False, True
4. False, False, False

Q2-1: Select the correct statement.

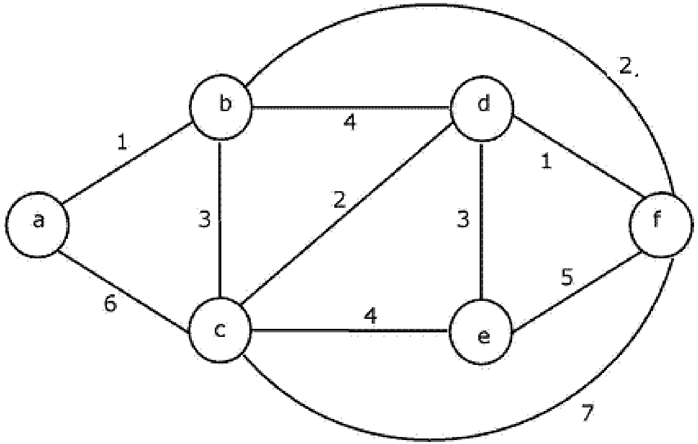
A. *The Chow-Liu algorithm not necessarily always choose edges from a complete graph.*
B. *The algorithm tries to find a minimum spanning tree of a graph to minimize the negative log-likelihood of training data.*
C. *Edge directions can be assigned randomly in the Chow-Liu algorithm.*

1. True, True, True
2. False, False, True
3. True, False, True
4. False, False, False ⬅

1. The Chow-Liu algorithm always have a complete graph.
2. The algorithm tries to find a maximum spanning tree of a graph to minimize the negative log-likelihood of training data.
3. Any directions for edges: Once we pick a node, and edges going away from this node, so that it remains a tree.

Q2-2: Which of the following can NOT be the sequence of edges added, in that order, to a maximum spanning tree using Kruskal's algorithm?

1. (c - f), (a - c), (e - f), (b - d), (b - c)
2. (c - f), (a - c), (e - f), (c - e), (b - d)
3. (c - f), (a - c), (e - f), (b - d), (d - e)
4. All of the above are valid.



Q2-2: Which of the following can NOT be the sequence of edges added, in that order, to a maximum spanning tree using Kruskal's algorithm?

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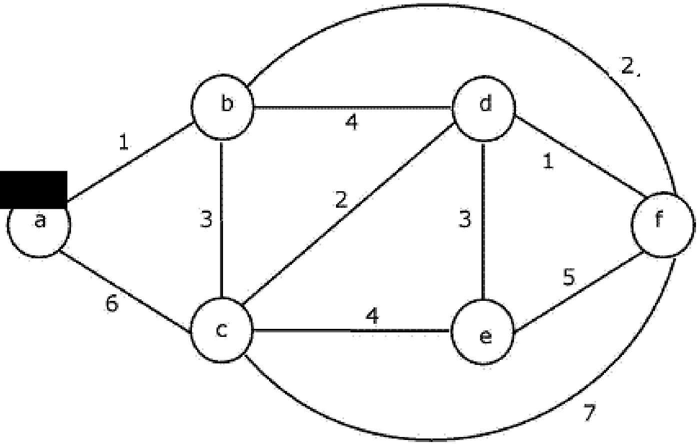
2. (c - f), (a - c), (e - f), (c - e), (b - d)
3. (c - f), (a - c), (e - f), (b - d), (d - e)
4. All of the above are valid.



(c - f), (a - c), **(e - f)**, **(c - e),** (b - d) form a cycle.

Q3-1: Select the correct statement.

A. *Sparse Candidate Algorithm (SCA) is an iterative algorithm.*
B. *SCA consists of 2 parts: Restrict Phase and Maximize Phase.*
C. *SCA will always lead to a global optimal solution.*

1. True, True, True
2. True, False, True
3. True, True, False
4. False, True, False

Q3-1: Select the correct statement.

A. *Sparse Candidate Algorithm (SCA) is an iterative algorithm.*
B. *SCA consists of 2 parts: Restrict Phase and Maximize Phase.*
C. *SCA will always lead to a global optimal solution.*

1. True, True, True
2. True, False, True
3. True, True, False ←
4. False, True, False

SCA can lead to sub-optimal solution.

Q3-2: Recall for Bernoulli distribution: Let X ~ Bern(θ), $x \in \{0, 1\}$, $0 < \theta < 1$. Then, $p_\theta(x) = \theta^x(1 - \theta)^{1-x}$ and $E[X] = \theta$. Consider two bernoulli distributions $p_{\theta 1}(X)$ and $p_{\theta 2}(X)$. Calculate the KL divergence: $KL(p_{\theta 1}(X) \,||\, p_{\theta 2}(X))$.

1. $\theta_1 \log[\theta_1/\theta_2] + (1 - \theta_1) \log[(1 - \theta_1)/(1 - \theta_2)]$
2. $\theta_2 \log[\theta_1/\theta_2] + (1 - \theta_2) \log[(1 - \theta_1)/(1 - \theta_2)]$
3. $(1 - \theta_1) \log[\theta_1/\theta_2] + \theta_1 \log[(1 - \theta_1)/(1 - \theta_2)]$
4. $(1 - \theta_2) \log[\theta_1/\theta_2] + \theta_2 \log[(1 - \theta_1)/(1 - \theta_2)]$

$$D_{KL}(P(X) \,||\, Q(X)) = \sum_x P(x) \log \frac{P(x)}{Q(x)}$$

Q3-2: Recall for Bernoulli distribution: Let $X \sim \text{Bern}(\theta)$, $x \in \{0, 1\}$, $0 < \theta < 1$. Then, $p_\theta(x) = \theta^x(1 - \theta)^{1-x}$ and $E[X] = \theta$. Consider two bernoulli distributions $p_{\theta 1}(X)$ and $p_{\theta 2}(X)$. Calculate the KL divergence: $KL(p_{\theta 1}(X) \,||\, p_{\theta 2}(X))$.

1. $\theta_1 \log[\theta_1/\theta_2] + (1 - \theta_1) \log[(1 - \theta_1)/(1 - \theta_2)]$ ←
2. $\theta_2 \log[\theta_1/\theta_2] + (1 - \theta_2) \log[(1 - \theta_1)/(1 - \theta_2)]$
3. $(1 - \theta_1) \log[\theta_1/\theta_2] + \theta_1 \log[(1 - \theta_1)/(1 - \theta_2)]$
4. $(1 - \theta_2) \log[\theta_1/\theta_2] + \theta_2 \log[(1 - \theta_1)/(1 - \theta_2)]$

Log-Likelihood Ratio (LLR)
$= \log[p_{\theta 1}(X)/p_{\theta 2}(X)]$
$= \log[\theta_1^X(1 - \theta_1)^{1-X} / \theta_2^X(1 - \theta_2)^{1-X}]$
$= X \log[\theta_1/\theta_2] + (1 - X) \log[(1 - \theta_1)/(1 - \theta_2)]$

$KL(p_{\theta 1}(x) \,||\, p_{\theta 2}(x)) = E_{\theta 1}(LLR)$
$= E_{\theta 1}[X] \log[\theta_1/\theta_2] + (1 - E_{\theta 1}[X]) \log[(1 - \theta_1)/(1 - \theta_2)]$
$= \theta_1 \log[\theta_1/\theta_2] + (1 - \theta_1) \log[(1 - \theta_1)/(1 - \theta_2)]$