# PH-2022 40-52

1

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- 1) Consider performing depth-first search (DFS) on an undirected and unweighted graph G starting at vertex s. For any vertex u in G, d[u] is the length of the shortest path from s to u. Let (u, v) be an edge in G such that d[u] < d[v]. If the edge (u, v) is explored first in the direction from u to v during the above DFS, then (u, v) becomes a <u>edge</u>.
  - a) tree
  - b) cross
  - c) back
  - d) gray
- 2) For any twice differentiable function  $f: \mathbb{R} \to \mathbb{R}$ , if at some  $x^* \in \mathbb{R}$ ,  $f'(x^*) = 0$  and  $f''(x^*) > 0$ , then the function f necessarily has a \_\_\_\_\_ at  $x = x^*$ .
  - a) local minimum
  - b) global minimum
  - c) local maximum
  - d) global maximum
- 3) Match the items in Column 1 with the items in Column 2 in the following table:

## Column 1

- (p) First In First Out
- (q) Lookup Operation
- (r) Last In First Out

- Column 2
- (i) Stacks
- (ii) Oueues
- (iii) Hash Tables
- a)  $(p) \rightarrow (ii), (q) \rightarrow (iii), (r) \rightarrow (i)$
- b) (p)  $\rightarrow$  (ii), (q)  $\rightarrow$  (i), (r)  $\rightarrow$  (iii)
- c) (p)  $\rightarrow$  (i), (q)  $\rightarrow$  (ii), (r)  $\rightarrow$  (iii)
- d) (p)  $\rightarrow$  (i), (q)  $\rightarrow$  (iii), (r)  $\rightarrow$  (ii)
- 4) Consider the dataset with six datapoints:  $\{(x_1, y_1), (x_2, y_2), \dots, (x_6, y_6)\}$ , where  $x_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, x_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$ ,  $x_3 = \begin{bmatrix} 0 \\ -1 \end{bmatrix}$ ,  $x_4 = \begin{bmatrix} -1 \\ 0 \end{bmatrix}$ ,  $x_5 = \begin{bmatrix} 2 \\ 2 \end{bmatrix}$ ,  $x_6 = \begin{bmatrix} -2 \\ -2 \end{bmatrix}$ , and the labels are given by  $y_1 = y_2 = y_5 = 1$ , and

 $y_3 = y_4 = y_6 = -1$ . A hard margin linear support vector machine is trained on the above dataset.

Which **ONE** of the following sets is a possible set of support vectors?

- a)  $\{x_1, x_2, x_5\}$
- b)  $\{x_3, x_4, x_5\}$
- c)  $\{x_4, x_5\}$
- d)  $\{x_1, x_2, x_3, x_4\}$
- 5) Match the items in Column 1 with the items in Column 2 in the following table:

#### Column 1

- (p) Principal Component Analysis
- (q) NaÃ-ve Bayes Classification
- (r) Logistic Regression

### Column 2

- (i) Discriminative Model
- (ii) Dimensionality Reduction
- (iii) Generative Model

- a) (p)  $\rightarrow$  (iii), (q)  $\rightarrow$  (i), (r)  $\rightarrow$  (ii)
- b) (p)  $\rightarrow$  (ii), (q)  $\rightarrow$  (i), (r)  $\rightarrow$  (iii)
- c) (p)  $\rightarrow$  (ii), (q)  $\rightarrow$  (iii), (r)  $\rightarrow$  (i)
- d) (p)  $\rightarrow$  (iii), (q)  $\rightarrow$  (ii), (r)  $\rightarrow$  (i)
- 6) Euclidean distance-based k-means clustering algorithm was run on a dataset of 100 points with k = 3. are both part of cluster 3, then which ONE of the following points is necessarily also part of cluster 3?
  - a)
- 7) Given a dataset with K binary-valued attributes (where K > 2) for a two-class classification task, the number of parameters to be estimated for learning a naA-ve Bayes classifier is
  - a)  $2^{K} + 1$
  - b) 2K + 1
  - c)  $2^{K+1} + 1$
  - d)  $K^2 + 1$

Here's the text of the questions and options from the image:

8) Consider performing uniform hashing on an open address hash table with load factor  $\alpha = \frac{n}{m} < 1$ , where n elements are stored in the table with m slots. The expected number of probes in an unsuccessful search is at most  $\frac{1}{1-\alpha}$ .

Inserting an element in this hash table requires at most \_\_\_\_\_ probes, on average.

- a)  $\ln\left(\frac{1}{1-\alpha}\right)$
- b)  $\frac{1}{1-\alpha}$  c)  $1 + \frac{\alpha}{2}$
- 9) For any binary classification dataset, let  $S_B \in \mathbb{R}^{d \times d}$  and  $S_W \in \mathbb{R}^{d \times d}$  be the between-class and withinclass scatter (covariance) matrices, respectively. The Fisher linear discriminant is defined by  $u^* \in \mathbb{R}^d$ , that maximizes

$$J(u) = \frac{u^T S_B u}{u^T S_W u}$$

If  $\lambda = J(u^*)$ ,  $S_W$  is non-singular and  $S_B \neq 0$ , then  $(u^*, \lambda)$  must satisfy which ONE of the following equations?

- a)  $S_w^{-1} S_B u^* = \lambda u^*$
- b)  $S_W u^* = \lambda S_B u^*$
- c)  $S_B S_W u^* = \lambda u^*$
- d)  $u^T u^* = \lambda^2$
- 10) Let  $h_1$  and  $h_2$  be two admissible heuristics used in  $A^*$  search.

Which ONE of the following expressions is always an admissible heuristic?

- a)  $h_1 + h_2$
- b)  $h_1 \times h_2$
- c)  $\frac{h_1}{h_2}(h_2 \neq 0)$

d) 
$$|h_1 - h_2|$$

11) Consider five random variables U, V, W, X, and Y whose joint distribution satisfies:

$$P(U, V, W, X, Y) = P(U)P(V)P(W|U, V)P(X|W)P(Y|W)$$

Which ONE of the following statements is FALSE?

- a) Y is conditionally independent of V given W
- b) X is conditionally independent of U given W
- c) U and V are conditionally independent given W
- d) Y and X are conditionally independent given W
- 12) Consider the following statement:

In adversarial search,  $\alpha \hat{a} \beta$  pruning can be applied to game trees of any depth where  $\alpha$  is the (m) value choice we have formed so far at any choice point along the path for the MAX player and  $\beta$  is the (n) value choice we have formed so far at any choice point along the path for the MIN player. Which ONE of the following choices of (m) and (n) makes the above statement valid?

- a) (m) = highest, (n) = highest
- b) (m) = lowest, (n) = highest
- c) (m) = highest, (n) = lowest
- d) (m) = lowest, (n) = lowest
- 13) Consider a database that includes the following relations:

Defender(name, rating, side, goals)

Forward(name, rating, assists, goals)

Team(name, club, price)

Which ONE of the following relational algebra expressions checks that every name occurring in Team appears in either Defender or Forward, where  $\phi$  denotes the empty set?

- a)  $\Pi_{\text{name}}(\text{Team}) \setminus (\Pi_{\text{name}}(\text{Defender}) \cap \Pi_{\text{name}}(\text{Forward})) = \phi$
- b)  $(\Pi_{\text{name}}(\text{Defender}) \cap \Pi_{\text{name}}(\text{Forward})) \setminus \Pi_{\text{name}}(\text{Team}) = \phi$
- c)  $\Pi_{\text{name}}(\text{Team}) \setminus (\Pi_{\text{name}}(\text{Defender}) \cup \Pi_{\text{name}}(\text{Forward})) = \phi$
- d)  $(\Pi_{\text{name}}(\text{Defender}) \cup \Pi_{\text{name}}(\text{Forward})) \setminus \Pi_{\text{name}}(\text{Team}) = \phi$