CS7641 ML Practice Quiz

Module SL 8: VC Dimensions

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Question 1

Which of the following statements correctly reflect the concepts discussed in VC Dimensions?
A. The number of samples needed to learn a classifier is inversely proportional to the size of the hypothesis space.
B. The formula for bounding the number of samples needed includes ε, representing the error parameter, and δ, representing the failure parameter.
C. In machine learning, it's established that all hypothesis spaces are finite.
D. The VC dimension of a hypothesis space does not influence the amount of data required for effective learning.
E. In VC dimensions, the concept of shattering is used to determine the largest set of inputs that a hypothesis space can label in all possible ways.

Question 2

Regarding the characteristics and implications of hypothesis spaces, which of the following are true?
A. All machine learning hypothesis spaces, including linear separators and neural networks, are finite.
B. The hypothesis space of k-nearest neighbors (k-NN) is subject to interpretation and may be considered either finite or infinite.
C. The VC dimension is irrelevant in determining the power of a hypothesis space.
D. For a hypothesis space, the largest set of inputs it can label in all possible ways is a measure of its power.
E. In hypothesis spaces, syntactically infinitely many functions can always be represented by a finite set of semantically different functions.

Question 3

Concerning the concept of VC dimensions and linear separators, which statements are correct?
A. The VC dimension of linear separators is determined to be 4 in two-dimensional space.
B. The VC dimension for linear separators can be easily determined in three-dimensional space.
C. Linear separators are defined by a weight parameter, w, and a threshold, theta, which create a line separating positive and negative examples.
D. In a two-dimensional space, three points on a number line can always be separated by a linear separator.
E. The VC dimension of linear separators is determined to be 3 in two-dimensional space.

Question 4

What are the key aspects and implications of VC dimensions in machine learning?

A. The VC dimension is unrelated to the number of parameters needed to represent hypothesis spaces.
B. The VC dimension of a d-dimensional hyperplane concept is d + 1.
C. Convex polygons have a finite VC dimension.
D. The sample complexity in machine learning is not connected to the VC dimension of a hypothesis class.
E. The VC dimension plays a similar role to the natural log of the size of the hypothesis space in finite cases.

Question 5

Regarding the relationship between VC dimensions and finite hypothesis spaces, which of the following statements are accurate?
A. The VC dimension of a finite hypothesis class is always greater than the logarithm base 2 of the size of the hypothesis class.
B. If the VC dimension of a hypothesis class is finite, then the class cannot be PAC-learnable.
C. The relationship between the size of a finite hypothesis class and its VC dimension is logarithmic.
D. A finite hypothesis class with an infinite VC dimension is PAC-learnable.
E. For a finite hypothesis class, the concept of PAC-learnability is unrelated to its VC dimension.

Answer Key

1. B, E
2. B, D
3. C, E
4. B, E
5. C