CSP 571 Data Preparation and Analysis

Quiz - 4

Question 1
In a support vector machine, in order to allow for non-linear decision boundaries, the expansion of feature space with non-linear functions of the predictors is accomplished via a
○ a. margin
○ b, hyperplane
○ c. vector
⊕ d. kernel
Question 2
The process of building a tree via recursive binary splitting of the predictor space in a top-down approach involves making a
o a, sub-optimal choice.
b. greedy choice.
○ c, gradient optimal choice.
○ d, globally optimal choice.
Question 3
In a support vector classifier, a training observation x_i that is on the correct side of the separating hyperplane but on the incorrect side of the margin will have a slack variable value of
\bigcirc a. $1 < \varepsilon_i$
\bigcirc b.0 $\leq \varepsilon_{i} < 1$
\odot c. $0 < \varepsilon_i \le 1$
$\bigcirc d.\varepsilon_{i} \leq 0$
Question 4 10 poi
Given a hyperplane which divides a p dimensional space into two halves, from which we can perform classification of an arbitrary point x , the hyperplane itself is an <i>affine subspace</i> of the below number of dimensions
■ a. p – 1
○ b. p + 1
O c. p
○ d.0
Question 5
The representation of a support vector machine as $f(x) = \beta_0 + \sum_{i=1}^n \alpha_i K(x, x_i)$ will result in what value for α_i for <i>training</i> observations which are <u>not support vectors</u>
● a. ()
○ b. ∞
○ c. −1
O d. 1
Question 6
Random forests improve upon bagging results by de-correlating accross bagged trees, via reduction of the number of
a, predictors considered at each split.
 ○ b, branches considered at each split.
○ c. observations considered at each split.
○ d. nodes considered at each split.

Decision tree methods split the predictor space into a series of non-overlapping regions R_j , each of which maps to a a. internal node. b. chlorophyll node. c. leaf/terminal node. d. root node. Question 9 When inducing a classification tree, a node that is more pure will have both Gini and Entropy values that are a. infinite compared to other nodes. b. lower than compared to other nodes. c. negative compared to other nodes. d. higher than compared to other nodes.	Question 7
 b. sum of each tree's predicted value. c. average of each tree's predicted value. d. maximum of each tree's predicted value. Question 8 Decision tree methods split the predictor space into a series of non-overlapping regions R _j , each of which maps to a a. internal node. b. chlorophyll node. c. leaf/terminal node. d. root node. Question 9 When inducing a classification tree, a node that is more pure will have both Gini and Entropy values that are a. infinite compared to other nodes. b. lower than compared to other nodes. c. negative compared to other nodes. d. higher than compared to other nodes. Question 10 In a maximal margin classifier, training data points which are directly related to the <u>potimal separation bysections</u> and would result in a different/changed hyperplane if they are altered are referred to as a. optimal vectors b. Invariant vectors c. kernel vectors 	Improving regression tree results via bagging involves B regression trees being induced from bootstrap samples, and final predictions being the
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○ b, margin vectors ○ c. kernel vectors	In a maximal margin classifier, training data points which are directly related to the optimal separating hyperplane and would result in a different/changed hyperplane if they are altered are referred to as
○ c. kernel vectors	o a, optimal vectors
	○ b, margin vectors
d, support vectors	○ c. kernel vectors
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