Unit 10 - Week 7 - Support Vector Machine (SVM)

Assignment 07

The due date for submitting this assignment has passed.
As per our records you have not submitted this assignment.

Due on 2019-09-18, 23:59 IST.

Instructions:

1. **Attempt all questions.**
2. **Submission deadline**: 18th September 2019 23:59 IST
3. **Solutions to be posted**: 19th September 2019
4. Older browsers might show **unnecessary vertical bars** at the end of math equations.

1) Which of the following are convex functions? *2 points*

- $f(x) = x^r$ for $r \geq 1$ and $0 < x < \infty$
- $f(x) = \log x$ for $0 < x < \infty$
- $f(x) = \frac{1}{x^r}$ for $r > 0$ and $0 < x < \infty$
- $f(x) = e^x$

No, the answer is incorrect.
Score: 0

Accepted Answers:
$f(x) = x^r$ for $r \geq 1$ and $0 < x < \infty$
$f(x) = \frac{1}{x^r}$ for $r > 0$ and $0 < x < \infty$
$f(x) = e^x$

2) Consider an optimization problem defined as *1 point*

$$\min_x \quad c^T x$$
$$\text{subject to} \quad Ax \leq b$$
$$x \geq 0$$

where $A \in \mathbb{R}^{m \times n}$, $c \in \mathbb{R}^n$ and $b \in \mathbb{R}^m$. Find the Lagrangian for the problem?

- $J(x, \alpha, \beta) = c^T x + \alpha^T (Ax - b) + \beta^T x$
- $J(x, \alpha, \beta) = c^T x + \alpha^T (Ax - b) - \beta^T x$
- $J(x, \alpha, \beta) = c^T x - \alpha^T (Ax - b) - \beta^T x$
- $J(x, \alpha, \beta) = c^T x - \alpha^T (Ax - b) + \beta^T x$

No, the answer is incorrect.
Score: 0

Accepted Answers:
$J(x, \alpha, \beta) = c^T x + \alpha^T (Ax - b) - \beta^T x$

3) In continuation with question 2, find the Lagrangian dual for the problem. *2 points*

- $\max_{\alpha,\beta} \quad \alpha^T A - \alpha^T b \quad \text{subject to} \quad c + A^T\alpha - \beta \geq 0 \quad \text{and} \quad \alpha \geq 0$
- $\max_{\alpha,\beta} \quad \alpha^T A - \alpha^T b - \beta \quad \text{subject to} \quad c - A^T\alpha - \beta \geq 0 \quad \text{and} \quad \alpha, \beta \geq 0$
- $\max_{\beta} \quad \beta^T x \quad \text{subject to} \quad c - A^T\beta \geq 0 \quad \text{and} \quad \beta \geq 0$
- $\max_{\alpha} \quad -\alpha^T b \quad \text{subject to} \quad c + A^T\alpha \geq 0 \quad \text{and} \quad \alpha \geq 0$

No, the answer is incorrect.
Score: 0

Accepted Answers:
$\max_{\alpha} \quad -\alpha^T b \quad \text{subject to} \quad c + A^T\alpha \geq 0 \quad \text{and} \quad \alpha \geq 0$

4) (True/False) Let the optimal hyperplane separating the data set be $w_o^T x + b_o = 0$. Then w_o is always orthogonal to the hyperplane. *1 point*

- True
- False

No, the answer is incorrect.
Score: 0

Accepted Answers:
True

5) Let $\{(x_i, d_i)\}_{i=1}^N$ be the training dataset and $\{x_1, x_2, x_3\}$ are the support vectors. The Lagrange for finding the optimal hyperplane for SVM is given as $J(w, b, \alpha) = \frac{1}{2} w^T w - \sum_{i=1}^N \alpha_i \left[d_i(w^T x_i + b) - 1\right]$. Then, $\sum_{i=4}^N \alpha_i =$

No, the answer is incorrect.
Score: 0

Accepted Answers:
(Type: Numeric) 0

1 point

6) Consider the following set of data points in $\mathbb{R}^2$ belonging to two classes C_1 and C_2 respectively. *1 point*

$C_1 = \{(3,1)^T, (3,-1)^T, (6,1)^T, (6,-1)^T\} \leftarrow -1(\text{label})$
$C_2 = \{(1,0)^T, (0,1)^T, (0,-1)^T, (-1,0)^T\} \leftarrow +1(\text{label})$

(True/False) Two classes are linearly separable.

- True
- False

No, the answer is incorrect.
Score: 0

Accepted Answers:
True

7) (True/False) In continuation with question 6, suppose we decide to use SVM along with a kernel function on the input data, then a simple kernel function $\Phi(.)$ will be an identity function. *1 point*

- True
- False

No, the answer is incorrect.
Score: 0

Accepted Answers:
True

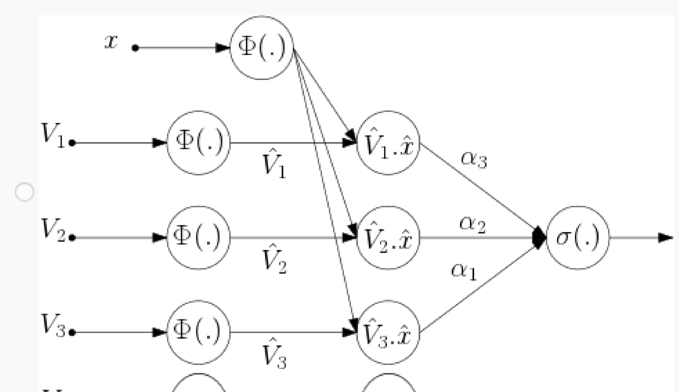
8) In continuation with questions 6 and 7, which of the following points are support vectors? *1 point*

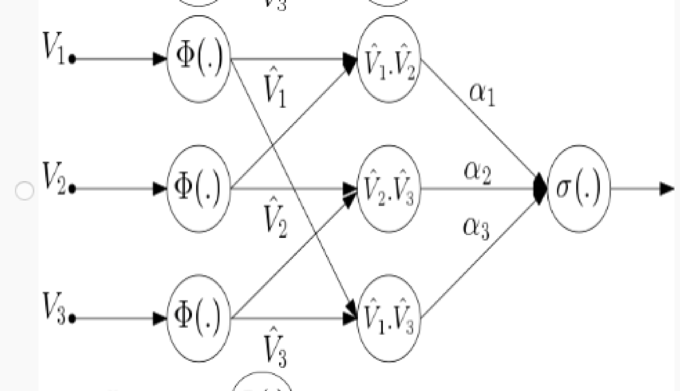
- $V_1 = (1,0)^T, V_2 = (3,1)^T, V_3 = (6,-1)^T$
- $V_1 = (6,1)^T, V_2 = (6,-1)^T, V_3 = (-1,0)^T$
- $V_1 = (1,0)^T, V_2 = (3,1)^T, V_3 = (3,-1)^T$
- $V_1 = (1,0)^T, V_2 = (3,1)^T, V_3 = (6,1)^T$

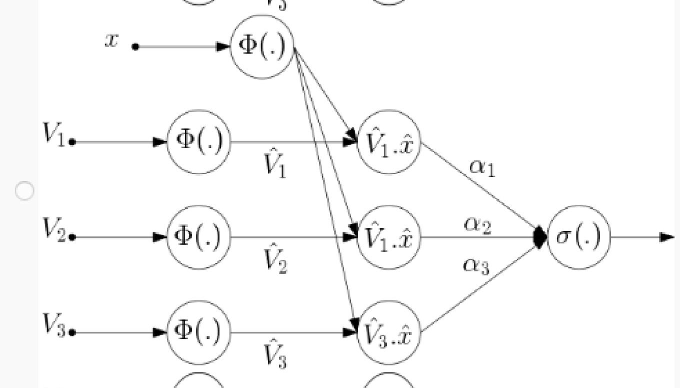
No, the answer is incorrect.
Score: 0

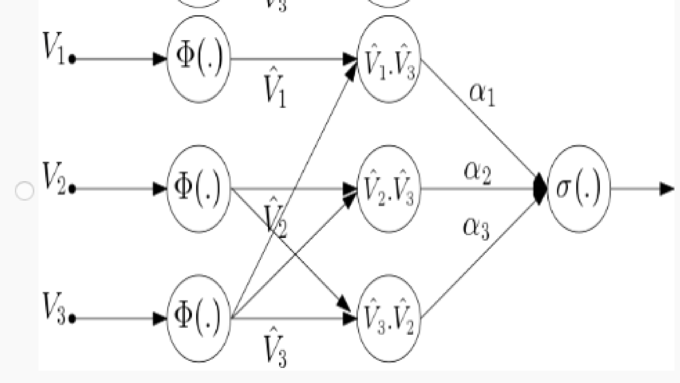
Accepted Answers:
$V_1 = (1,0)^T, V_2 = (3,1)^T, V_3 = (3,-1)^T$

9) In continuation with questions 6, 7, and 8, let us augment a "1" to the set of data points as a bias input, that is, $V_1 = (1,0)^T$ becomes $\hat{V}_1 = (1,0,1)^T$. With these new set of data points, the SVM architecture is *2 points*



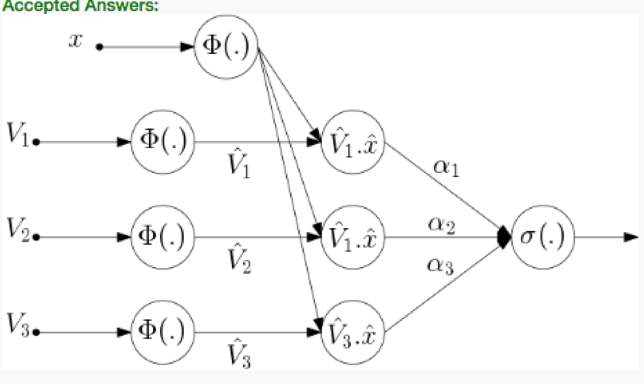






No, the answer is incorrect.
Score: 0

Accepted Answers:



10) In continuation with questions 6, 7, 8, and 9, now the goal is to find α_1, α_2 and α_3 such that *3 points*

- $2\alpha_1 + 4\alpha_2 + 4\alpha_3 = -1$
  $4\alpha_1 + 11\alpha_2 + 9\alpha_3 = +1$
  $4\alpha_1 + 9\alpha_2 + 11\alpha_3 = +1$
- $2\alpha_1 + 4\alpha_2 + 4\alpha_3 = -1$
  $4\alpha_1 + 11\alpha_2 + 11\alpha_3 = +1$
  $4\alpha_1 + 9\alpha_2 + 9\alpha_3 = +1$
- $2\alpha_1 + 4\alpha_2 + 2\alpha_3 = -1$
  $4\alpha_1 + 11\alpha_2 + 11\alpha_3 = +1$
  $4\alpha_1 + 9\alpha_2 + 9\alpha_3 = +1$
- $2\alpha_1 + 4\alpha_2 + 4\alpha_3 = -1$
  $4\alpha_1 + 11\alpha_2 + 9\alpha_3 = +1$
  $4\alpha_1 + 2\alpha_2 + 11\alpha_3 = +1$

No, the answer is incorrect.
Score: 0

Accepted Answers:
$2\alpha_1 + 4\alpha_2 + 4\alpha_3 = -1$
$4\alpha_1 + 11\alpha_2 + 9\alpha_3 = +1$
$4\alpha_1 + 9\alpha_2 + 11\alpha_3 = +1$

11) In continuation with questions 6, 7, 8, 9, and 10, the equation of the hyperplane is $y = w^T x + b$ where w and b are *2 points*

- $w = (1,0)^T$ and $b = -1$
- $w = (-1,0)^T$ and $b = 0$
- $w = (1,0)^T$ and $b = -2$
- $w = (-1,0)^T$ and $b = -2$

No, the answer is incorrect.
Score: 0

Accepted Answers:
$w = (1,0)^T$ and $b = -2$

12) In class, we considered a single inequality constraint optimization problem. Now consider a minimization problem with two inequality constraints as given below: *3 points*

$$\min \quad f(x_1, x_2) = x_1 + x_2$$
$$\text{s.t.} \quad 4 - 2x_1^2 - 2x_2^2 \geq 0$$
$$2x_2 \geq 0$$

The Lagrange multipliers at minimum solution point $x^\star$ are λ_1 and λ_2, then $\lambda_1 + \lambda_2$ is

- $\frac{1}{2} + 1$
- $\frac{1}{\sqrt{2}} + 1$
- $\frac{2}{\sqrt{2}} + 1$
- $\frac{1}{2\sqrt{2}} + 1$

No, the answer is incorrect.
Score: 0

Accepted Answers:
$\frac{1}{2\sqrt{2}} + 1$