

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

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## Assignment 07

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

Due on 2019-09-16, 23:59 IST.

### Instructions:

- Attempt all questions.
- Submission deadline: 18th September 2019 23:59 IST
- Solutions to be posted: 19th September 2019
- 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  $0 < x < \infty$
- $f(x) = \frac{1}{x}$  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  $0 < x < \infty$   
 $f(x) = \frac{1}{x}$  for  $r > 0$  and  $0 < x < \infty$   
 $f(x) = e^x$

2) Consider an optimization problem defined as 1 point

$$\min_x c^T x$$

subject to  $Ax \leq b$   
 $x \geq 0$

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?

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

No, the answer is incorrect. Score: 0

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

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

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

No, the answer is incorrect. Score: 0

Accepted Answers:  
 $\max_x -a^T b$  subject to  $c + A^T \alpha \geq 0$  and  $\alpha \geq 0$

4) (True/False) Let the optimal hyperplane separating the data set be  $w_0^T x + b_0 = 0$ . Then  $w_0$  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  $J(w, b, \alpha) = \frac{1}{2} w^T w - \sum_{i=1}^N \alpha_i [d_i (w^T x_i + b) - 1]$ . Then,  $\sum_{i=1}^N \alpha_i =$

No, the answer is incorrect. Score: 0

Accepted Answers:  
 (Type: Numeric) 0

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

$C_1 = \{(3, 1)^T, (3, -1)^T, (6, 1)^T, (6, -1)^T\} \leftarrow -1$  (label)  
 $C_2 = \{(1, 0)^T, (0, 1)^T, (0, -1)^T, (-1, 0)^T\} \leftarrow +1$  (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  $\Phi(\cdot)$  will be an identity function. 1 point

- True
- False

No, the answer is incorrect. Score: 0

Accepted Answers:  
 True

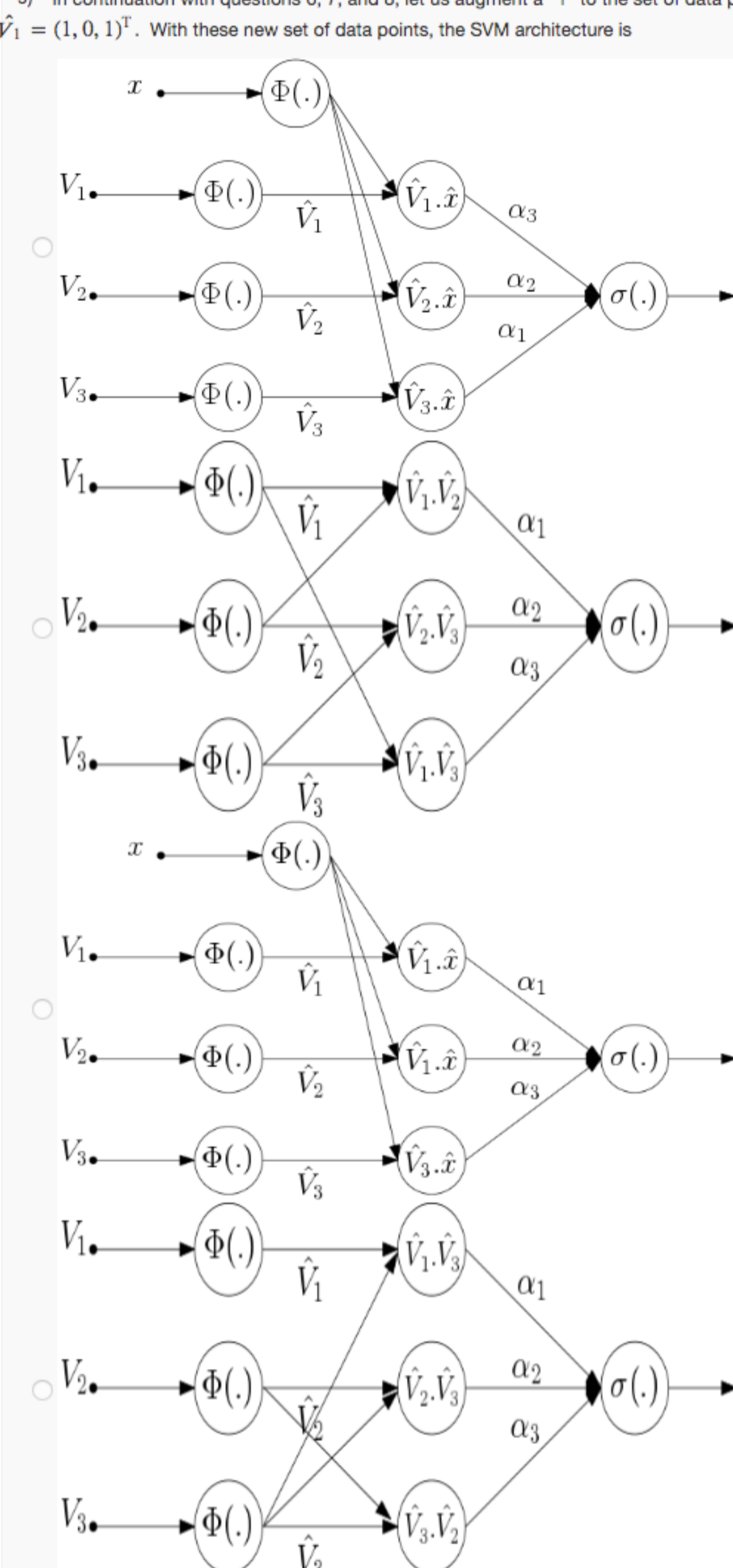
8) In continuation with questions 6 and 7, which of the following points are support vectors? 1 point

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

No, the answer is incorrect. Score: 0

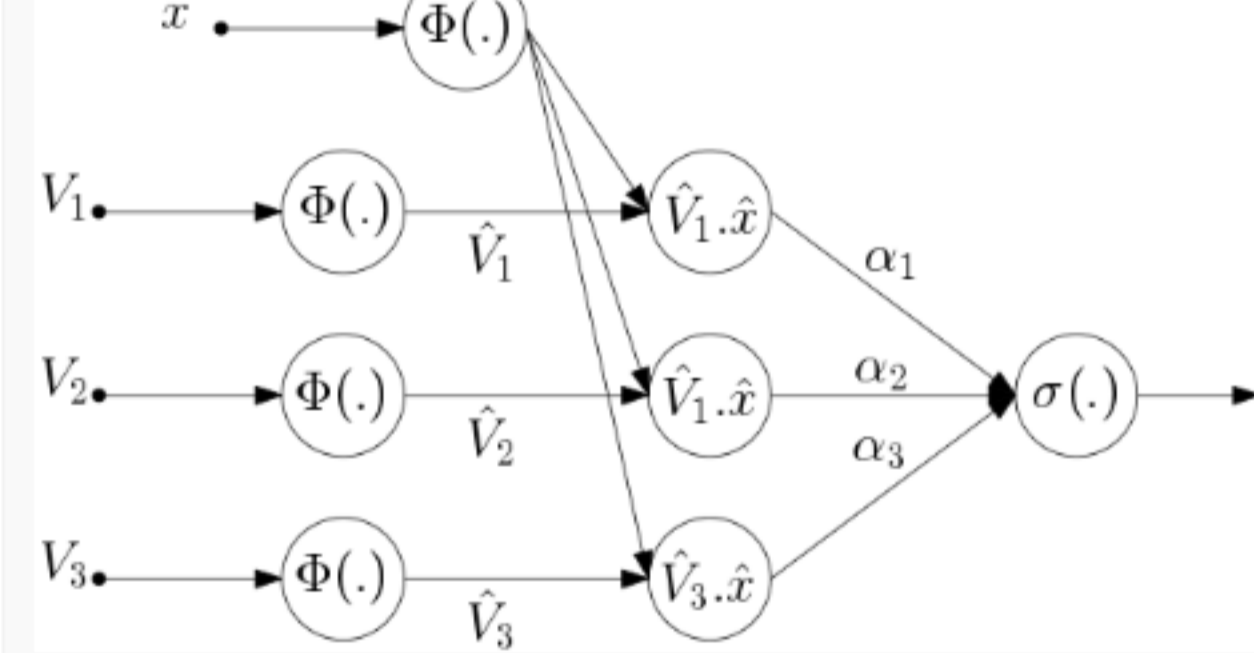
Accepted Answers:  
 $V_1 = (1, 0)^T, V_2 = (3, 1)^T, V_3 = (3, -1)^T$

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



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  $\alpha_1, \alpha_2$  and  $\alpha_3$  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

$$\min f(x_1, x_2) = x_1 + x_2$$

s.t.  $4 - 2x_1^2 - 2x_2^2 \geq 0$   
 $2x_2 \geq 0$

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

- $\frac{1}{2} + 1$
- $\frac{1}{\sqrt{2}} + 1$
- $\frac{3}{2} + 1$
- $\frac{3}{\sqrt{2}} + 1$
- $\frac{1}{2\sqrt{2}} + 1$

No, the answer is incorrect. Score: 0

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