

# ML Homework 3

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## 1 Kernels

### 1.1

We know the given kernel putting these values in the kernel we get

$$K(x, x') = \begin{cases} 1, & \text{if } x = x' \\ 0, & \text{otherwise} \end{cases} \implies K = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & . & . & . & 0 \\ . & . & . & . & . & . \\ 0 & . & . & . & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

To get a valid kernel we should have  $\alpha^T K \alpha \geq 0$

$$\alpha^T K \alpha = \begin{bmatrix} a_1 & a_2 & a_3 & . & a_n \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & . & . & . & 0 \\ . & . & . & . & . & . \\ 0 & . & . & . & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ . \\ a_n \end{bmatrix}$$

Hence we get  $a_1^2 + a_2^2 + a_3^2 + \dots + a_n^2 \geq 0$ . This matrix is positive and semidefinite.

Hence we can say that this is a valid kernel

## 1.2

$$J(\alpha) = \frac{1}{2}\alpha^T K^T K \alpha - y^T K \alpha + \frac{1}{2}y^T y \quad \text{since } \lambda = 0$$

$$\frac{\partial J(\alpha)}{\partial \alpha} = \alpha^T K^T K - y^T K = 0 \quad \text{Differentiating w.r.t } \alpha$$

$$\implies \alpha^T K^2 - y^T K = 0$$

$$\implies \alpha^* = K^{-1}y$$

$$\text{Hence } \alpha^* = y \quad \text{Since } K^{-1} = K = I$$

## 1.3

$$\text{Given, } f(x) = k(x, x_1), k(x, x_2) \dots k(x, x_N) \alpha^*$$

$$\text{We know for any } x \neq x_n, k(x, x') = 0$$

$$\text{Hence we get, } f(x) = [0^* \ 0^* \ 0^* \ \dots \ 0] \alpha^*$$

$$\implies f(x) = 0$$

$$\text{Thus for any } x \neq x_n \text{ prediction is always } 0$$

# 2 Support Vector Machines

## 2.1

No the data is not linearly separable in this one dimensional space

$$\text{We know } y[w^T x + b] \leq 0 \implies \begin{cases} w^T - b & x = -1 \text{ and } y = -1 \\ b, & x = 0 \text{ and } y = 1 \\ -w^T - b & x = 1 \text{ and } y = -1 \end{cases}$$

From above case (1) and case (3)  $w^T - b \leq 0$ ,  $b \leq 0$  and  $-w^T - b \leq 0$  they contradict

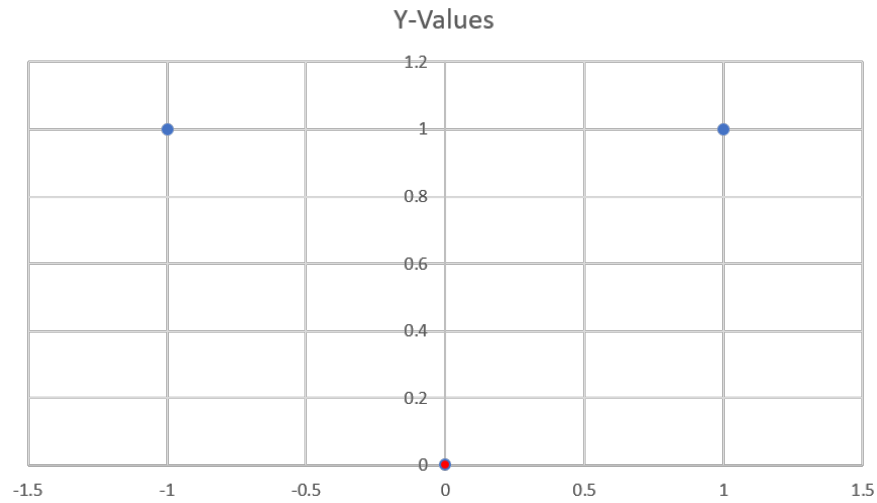
We need two decision boundaries to separate the data in 1-D feature space

Hence data is not separable

## 2.2

Yes there exists a boundary after transferring from 1D space to 2D space

New point in new space are  $b > w, b > -w, b > 0$



## 2.3

$$k = \phi(x)^T \phi(x') \quad \phi(x) = \begin{pmatrix} x \\ x^2 \end{pmatrix}$$

$$\implies k = x * x' + x^2 * (x')^2$$

$$\implies K = \begin{bmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad \text{let } z = \begin{bmatrix} l \\ m \\ n \end{bmatrix} \quad z \text{ is non zero column vector}$$

For K to be a postive semi definite,  $z^T M z > 0$

$$\begin{bmatrix} l & m & n \end{bmatrix} \begin{bmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} l \\ m \\ n \end{bmatrix} = 2l^2 + 2m^2 > 0$$

Hence  $z^T M z > 0$

## 2.4

$$\text{Primal formula} = \min_w \frac{1}{2} \|w\|_2^2$$

$$s.t \quad w^T \begin{bmatrix} -1 & 1 \end{bmatrix}^T + b \leq -1$$

$$w^T \begin{bmatrix} 1 & -1 \end{bmatrix}^T + b \leq -1$$

$$b \geq 1$$

$$\text{Dual formula} = \min_{\alpha} L(\alpha) = \min_{\alpha} \alpha_1^2 + \alpha_2^2 - \alpha_1 - \alpha_2 - \alpha_3$$

$$s.t \quad \alpha_1 \geq 0 \quad \alpha_2 \geq 0 \quad \alpha_3 \geq 0$$

$$-\alpha_1 - \alpha_2 + \alpha_3 = 0$$

## 2.5

$$J(\alpha) = \min_{\alpha} \frac{1}{2} \sum_{m,n}^3 y_m y_n \alpha_m \alpha_n \phi(x_m) \phi(x_n) - \sum_n^3 \alpha a_n$$

$$y_1 \alpha_1 + y_2 \alpha_2 + y_3 \alpha_3 = 0$$

We know  $y_1 = -1, y_2 = -1, y_3 = 1$

$\Rightarrow$  By symmetry  $\alpha_1 = \alpha_2$  and  $\alpha_3 = 2\alpha_1$

$\Rightarrow \min_{\alpha} \frac{1}{2} (2\alpha_1^2 + 2\alpha_2^2) - (\alpha_1 + \alpha_2 + \alpha_3)$  using dual formation

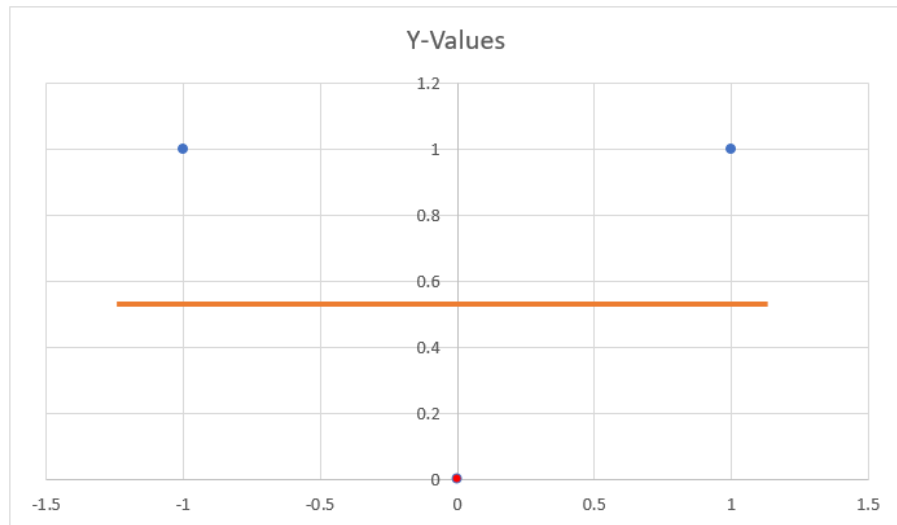
$$\frac{\partial J(\alpha)}{\partial \alpha} = 4(\alpha_1 - 1) = 0 \quad \text{now diff w.r.t } \alpha$$

$$\Rightarrow \alpha_1 = 1, \alpha_2 = 1, \alpha_3 = 2$$

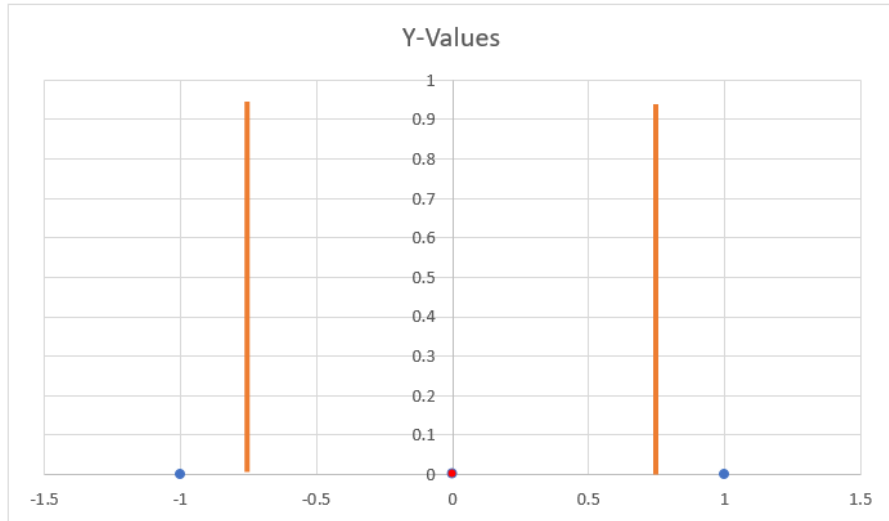
$$w = \sum y_n \alpha_n \phi(x_n) = [0, -2]^T$$

$$b = y_n - \sum_{m=1}^3 y_m \alpha_m k(x_m, x_n) = 1$$

## 2.6



Two dimensional Space



One dimensional Space

The circled points are the support vectors

First plot  $x^2 = 0.5$  is the decision boundary in the 2-D feature space

Second plot  $x = 0.707$  and  $x = -0.707$  is the the decision boundaries in 1-D feature space

## 3 Adaboost

### 3.1

$$f_1(s, b, d) = (1, 0.5, -1)$$

$$\epsilon_1 = 0.50 \quad \beta_1 = 0$$

### 3.2

$$w_2(1) = 0.25 \quad w_2(2) = 0.25 \quad w_2(3) = 0.25 \quad w_2(4) = 0.25$$

$$\implies w_2(n) = [0.25 \quad 0.25 \quad 0.25 \quad 0.25]$$

### 3.3

$$f_1(s, b, d) = (1, -0.5, 1)$$

$$\epsilon_1 = 0.25 \quad \beta_1 = 0.55$$

### 3.4

$$f_2(s, b, d) = (1, 0.5, 2)$$

$$\epsilon_2 = 0.17 \quad \beta_2 = 0.79$$

$$w_2(n) = [0.17 \quad 0.17 \quad 0.17 \quad 0.49]$$

### 3.5

$$f_3(s, b, d) = (-1, -0.5, 2)$$

$$\epsilon_3 = 0.1 \quad \beta_3 = 1.1$$

$$w_3(n) = [0.10 \quad 0.10 \quad 0.50 \quad 0.30]$$

### 3.6

$$F(x) = \text{sign}[0.55 * h_{(1, -0.5, 1)}(x) + 0.807 * h_{(1, 0.5, 2)}(x) + 0.109 * h_{(-1, -0.5, 2)}(x)]$$

$$F(x_1) = 1 \quad F(x_2) = -1 \quad F(x_3) = 1 \quad F(x_4) = -1$$

$$\implies F(x) = [1 \quad -1 \quad 1 \quad -1]$$

All are labeled correctly