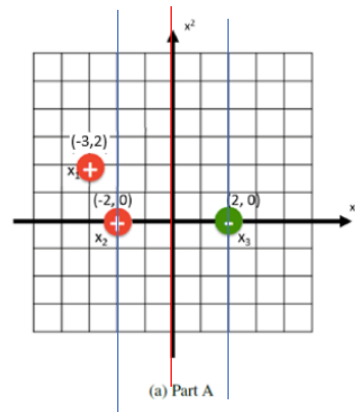


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Subject – CSE 575 SML Fall 2022

## Q1. Support Vector Machine.

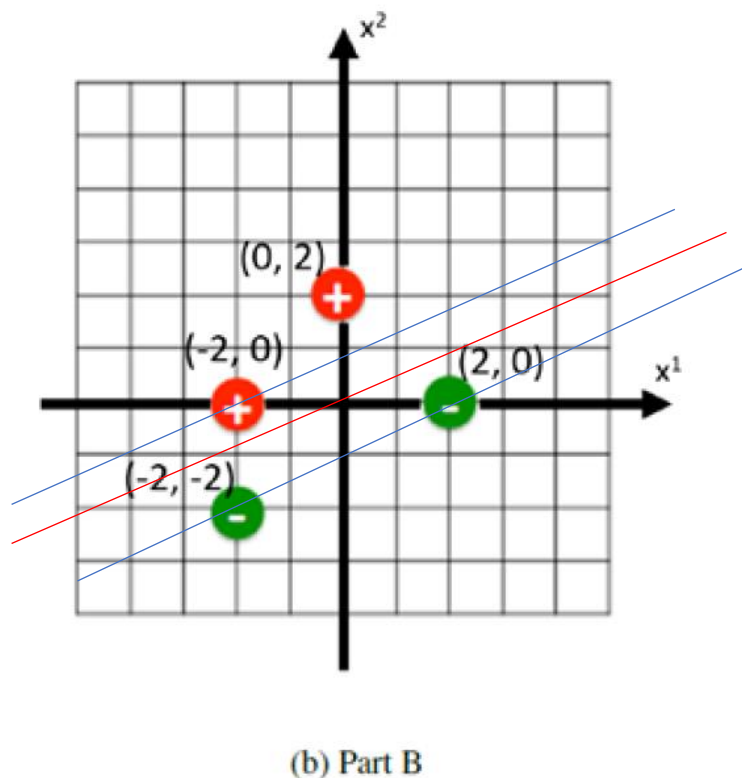
1.1 For each figure 1(a) ,the support vectors are  $x_2$  and  $x_3$ .

The margin is 2.



For the case of figure 1(b), the support vectors are the two negative data points and one positive data point at  $(-2,0)$ .

The margin is  $\frac{2}{\sqrt{5}}$ .



**1.2** The primal optimization solution is given by,

$W = [w_1, w_2]^T$ , putting the coordinates of training data to the equation.

$$\min \frac{1}{2} \|W\|^2 \text{ s.t. } t_n(w^T x_n + b) \geq 1; n = 1, 2, 3, \dots, N$$

with  $x_1 = [-2, 2]^T, x_2 = [-2, 0]^T$ ,

and  $x_3 = [2, 0]^T$ . We have the primal problem

$$\min \frac{1}{2} (W_1 + W_2)^2$$

$$\text{s.t. } -2w_1 + 2w_2 + b \geq 1$$

$$-2w_1 + b \geq 1$$

$$-2w_1 - b \geq 1$$

The Lagrangian function is given by,

$$L(w, b, a) = \frac{1}{2} (W_1^2 + W_2^2) - a_1(-2w_1 + 2w_2 + b - 1) - a_2(-2w_1 + b - 1) - a_3(-2w_1 - b - 1)$$

Now substitute training coordinates to general formula of dual problem.

$$L(a) = \sum_{n=1}^N a_n - \frac{1}{2} \sum_{n=1}^N \sum_{m=1}^N a_n a_m t_n t_m \phi^T(\mathbf{x}_n) \phi(\mathbf{x}_m)$$

$$\text{s.t. } a_n > 0; n = 1, 2, 3, \dots, N$$

$$\sum_{n=1}^N a_n t_n = 0$$

**We have the dual optimization for this problem.**

**max value is**

$$-\frac{1}{2}(8a_1^2 + 4a_2^2 + 4a_3^2 + 8a_1a_2 + 8a_1a_2 + 8a_2a_3) + a_1 + a_2 + a_3$$

$$\text{s.t } a_1 \geq 0, a_2 \geq 0, a_3 \geq 0$$

$$-a_1 - a_2 + a_3 = 0$$

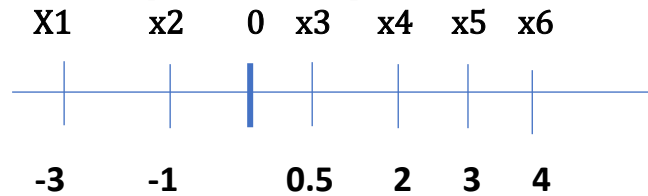
**1.3** The decision boundary is  **$x_1 = 1$** .  **$(x_1, x_2)$  will have label 1** if  $x_1 < 1$  and will have label -1 if  $x_1 > 1$ .

The decision boundary will not change due to the addition of new point, because it is on the left side of margin.

## Q2. K-means

**2.1** The given six data points  $x_1 = -3, x_2 = -1, x_3 = 0.5, x_4 = 2, x_5 = 3, x_6 = 4$ .

Plot of six data points in 1D space,



**2.2** For  $K = 2$ . Initial cluster centres  $\mu_1 = -1$  and  $\mu_2 = 3$ .

After Step 1, cluster 1 ( $\mu_1 = -1$ ) will contain points  $x_1, x_2, x_3$ .

cluster 2 ( $\mu_2 = 3$ ) will contain points  $x_4, x_5, x_6$ .

After Step 2,

$$\mu_k = \frac{\sum_n r_{nk} x_n}{\sum_n r_{nk}}.$$

**Applying the above formula we get,**

$$\mu_1 = \frac{-3 - 1 + 0.5}{3} = \frac{-3.5}{3} = -1.1667$$

$$\mu_2 = \frac{2 + 3 + 4}{3} = \frac{9}{3} = 3$$

**2.3** For  $K = 3$ , initial clusters  $\mu_1 = -3, \mu_2 = 0, \mu_3 = 3$

After step1, cluster 1 ( $\mu_1 = -3$ ) contains points  $x_1$ .

Cluster 2 ( $\mu_2 = 0$ ) contains points  $x_2, x_3$ .

Cluster 3 ( $\mu_3 = 3$ ) contains  $x_4, x_5, x_6$ .

After Step 2,

$$\mu_1 = -3$$

$$\mu_2 = \frac{-1 + 0.05}{2} = -0.25$$

$$\mu_3 = \frac{2 + 3 + 4}{3} = 3$$

The loss function J is calculated as follows,

$$J = \sum_{n=1}^N \sum_{k=1}^K r_{nk} \| \mathbf{x}_n - \mu_k \|^2$$

$$J = (-3 + 3)^2 + (-1 + 0.25)^2 + (0.05 + 0.25)^2 + \\ (-2 + 3)^2 + (-3 + 3)^2 + (-3 - 4)^2$$

$$\mathbf{J = 3.125}$$

**2.4** For K = 6, each point will form its own cluster.

$$\mathbf{J = 0}$$

### Q3. Unconstrained Optimization

The function is given by,

$$f(x) = x_1^2 + 5 \cdot x_2^2$$

**3.1** The gradient at point  $x' = [5, 1]^T$

Taking the differentiate of  $f(x)$ .

$$\nabla f(x) = \begin{bmatrix} 2 \cdot x_1 \\ 10 \cdot x_2 \end{bmatrix}$$

$$\nabla f(x') = \begin{bmatrix} 10 \\ 10 \end{bmatrix}$$

**3.2** Steepest descent direction at point  $x'$ ,

$$-\nabla f(x') = \begin{bmatrix} -10 \\ -10 \end{bmatrix}$$

**3.3** For backtrack line search at point  $x'$  along direction  $-\nabla f(x')$

Using  $\alpha = 0.4$  and  $\beta = 0.9$ .

To find the largest value of  $t$  such that,

$$f(x' - t\nabla f(x')) \leq f(x') - 0.4t \|\nabla f(x')\|^2$$

Solving the above equation for multiple values of  $t$ ,

Start with  $t = 1$ , then  $t \rightarrow t\beta$

$t \in \{1, 0.9, 0.9^2, 0.9^3, 0.9^4, \dots\}$

The computed step size is  $0.9^{16} \approx 0.185$

**3.4** To perform exact line search at point  $\mathbf{x}'$ ,  
 along the direction  $-\nabla f(\mathbf{x}')$ ,  
 the optimal value of  $t$  by solving the problem is given by,

$$\min \mathbf{f}(\mathbf{x}' - t\nabla f(\mathbf{x}'))$$

Which is given by,

$$\min 600 t^2 - 200 t + 30$$

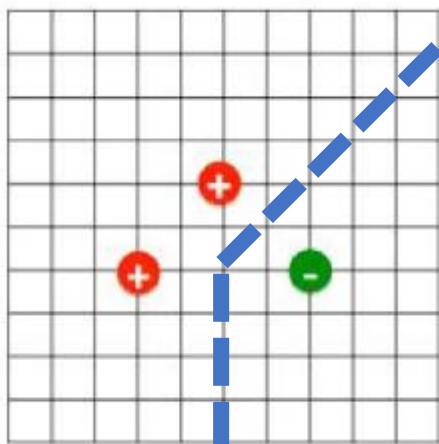
The computed step size is,

$$= \frac{1}{6}$$

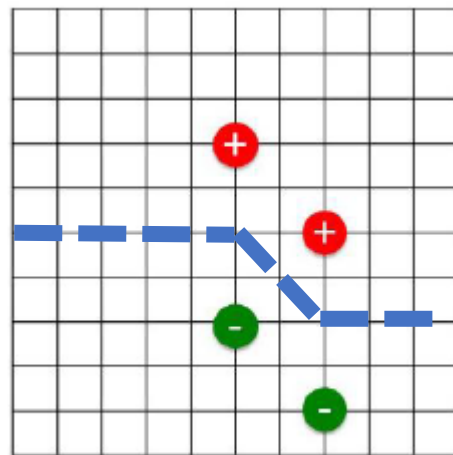
#### Q4. The Decision Boundary for 1NN.

Following the below steps for drawing Perpendicular bisector to draw the decision boundary.

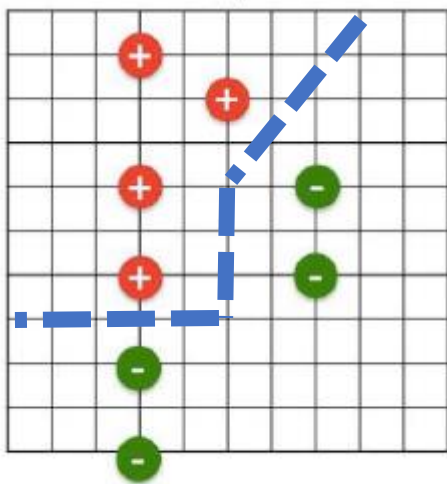
- Identify pairs of training points from different classes. ('+' or '-')
- Draw the perpendicular bisector for every segment connecting the points in a pair in step 1.
- Connect the perpendicular bisector to form a decision boundary.



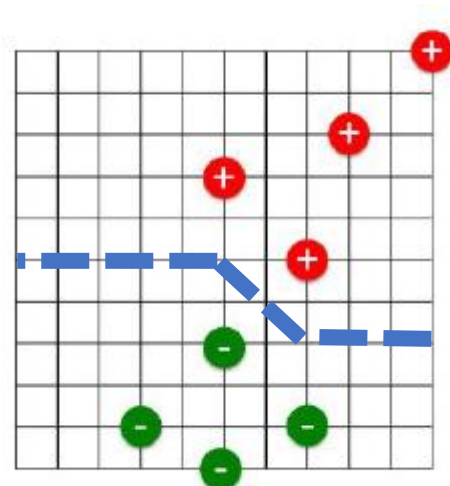
(a)



(b)



(c)



(d)