

Question 1

We have three training observations , x_1 , x_2 and x_3

X_1 represents the x values of the data set while X_2 represents the Y values of the data set

Since the data set is linearly separable , we know it has a hyperplane of the form

$$F(x) = W^T \cdot X - Y$$

Y represents the bias while W presents the weight vector

We know that the function yields a value \geq to zero when y takes the value 1 and a value \leq zero when y takes the value -1

So we know that training set (1,1) yields a value less than 0 when substituted in $f(x)$.

We also know that the training sets (2,2) and (3,1) yields a value greater than zero when substituted in $F(x)$

The training sets are separated by the function $f(x) = w^T x - Y = 0$

We locate the hyperplane that maximizes the separation between the two classes of x

To do this we find the unit vector w that minimizes a cost function $\frac{1}{2} (w^T) w = \frac{1}{2} \|w\|^2$,
subject to the constraints

$$Y_i (w^T \cdot x_i) \geq 1 ; \text{ where } i = 1, 2, 3, \dots, n$$

0.2 becomes the value of the unit vector that will maximize the cost function

The hyperplane $\{x : f(x) = W^T \cdot X - y\}$ divides the input space into two , and the sign of $f(x)$

The decision boundary will be the differentiation between the regions we have classified as positive and negative

Based on the classes of the inputs and the value of the weight vectors ,

The decision boundaries will be

$$F(x_+) = 0.2^T \cdot X - Y = 1 ,$$

$$\text{And } F(X_-) = 0.2^T \cdot X - Y = -1$$

Question Two

We want to prove that given $x = [x_1, x_2]^T$ and a Feature map $\Phi(x) = [1, x_1^2, \sqrt{2}x_1x_2, x_2^2, \sqrt{2}x_1, \sqrt{2}x_2]^T$ when given the kernel function as $k(x, z) = (X^T \cdot Z + 1)^2$

The general form of the feature vector is $\Phi(\cdot)$

We replace the dots with an equivalent kernel function

We know that

$$\Phi(X) = \Phi((x_1 \ x_2)) = (x_1^2 \ \sqrt{2}x_1x_2 \ x_2^2)$$

$$\text{Such that } k(x, x') = \Phi(x)^T \Phi(x')$$

$$\text{From the feature map } \Phi(x) = [1, x_1^2, \sqrt{2}x_1x_2, x_2^2, \sqrt{2}x_1, \sqrt{2}x_2]^T$$

And the X_1 and X_2 as the classes of inputs ,

Therefore to find $K(x, z)$,

We Write the general formula of the kernel function as

$$(X_i^T Y + Y_1)^2$$

X should represent the number of observation which are two , x and y

The function Y1 takes the value 1

We know that based of the mapping feature , z provides the range of inputs ,

Therefore

$$K(x,z) = (x^T \cdot \text{the value of } y + 1)^2$$

$$= (x^T z + 1)$$

Part B

We have four observations and two dimensions give as X1 and X2,

The observations (-1, -1) and (1, 1) provide a value of F(x) less than or equal to zero

The observation (-1, 1) and (1,-1) provide a value of F(x) greater than or Zero

The training sets are separated by the function $f(x) = w^T x - Y = 0$

We locate the hyperplane that maximizes the separation between the two classes of x

To do this we find the unit vector w that minimizes a cost function $\frac{1}{2} (w^T) w = \frac{1}{2} \|w\|^2$,

subject to the constraints

$$Y_i (w^T x_i) \geq 1 ; \text{ where } i = 1, 2, 3, \dots, n$$

We use the kernel valuable as the slack variable

We get the function

$$F(X.) = 0.2 \wedge T.X - Y + (X^{\wedge}T.Z + 1) \wedge 2$$