

# Support Vector Machines (SVMs)

## Task 1:

### Q1: What is the margin and support vectors?

Margin is the width a linear classifier could be increased before hitting any data points, and a support vector is a datapoint that the margin hits. (As defined in the powerpoints)

### Q2: How does SVM deal with non-separable data?

An SVM deals with non-separable data by using a soft margin that allows for some misclassification error, or mapping the features to a higher dimensional space where they are separable by some hyperplane. You can also use a kernel to make the data linearly separable.

### Q3: What is a kernel?

A kernel function calculates an inner product of the input features in order to make the data linearly separable.

### Q4: How does a kernel relate to feature vectors?

The kernel applies an inner product to the feature vectors using some function such as a polynomial, gaussian, sigmoid, etc...

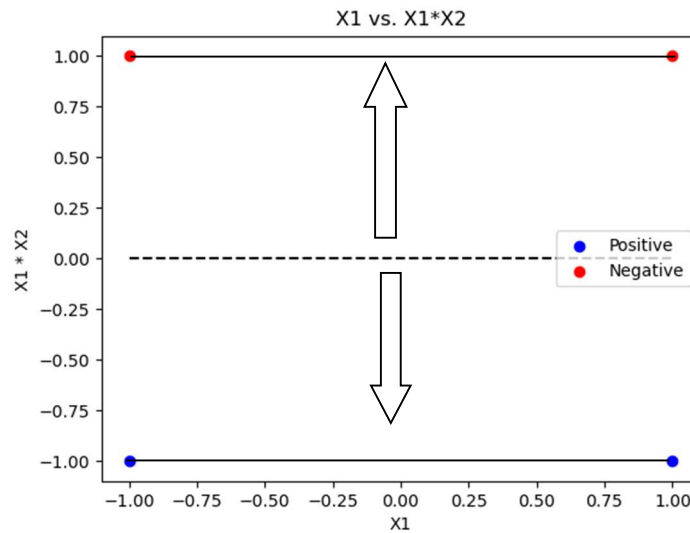
(I got these answers using the 5.3SVM2 powerpoint)

**Task 2: Construct a support vector machine that computes the kernel function. Use four values of +1 and -1 for both inputs and outputs:**

- $[-1, -1]$  (negative)
- $[-1, +1]$  (positive)
- $[+1, -1]$  (positive)
- $[+1, +1]$  (negative).

Map the input  $[x_1, x_2]$  into a space consisting of  $x_1$  and  $x_1x_2$ . Draw the four input points in this space, and the maximal margin separator. What is the margin?

- ➔ 1:  $X_1 = -1, X_2 = -1 \rightarrow X_1 = -1, X_1X_2 = +1$
- ➔ 2:  $X_1 = -1, X_2 = +1 \rightarrow X_1 = -1, X_1X_2 = -1$
- ➔ 3:  $X_1 = +1, X_2 = -1 \rightarrow X_1 = +1, X_1X_2 = -1$
- ➔ 4:  $X_1 = +1, X_2 = +1 \rightarrow X_1 = +1, X_1X_2 = +1$



➔ Margin = 1

**Task 3:** Recall that the equation of the circle in the 2-dimensional plane is  $(x_1 - a)^2 + (x_2 - b)^2 - r^2 = 0$ . Please expand out the formula and show that every circular region is linearly separable from the rest of the plane in the feature space  $(x_1, x_2, x_1^2, x_2^2)$ .

➔  $(x_1 - a)^2 + (x_2 - b)^2 - r^2 = 0$

➔  $X_1^2 - 2a*x_1 + a^2 + x_2^2 - 2b*x_2 + b^2 = 0$

➔  $X_1 = (X_1^2 + a^2 + x_2^2 - 2a*x_2 + b^2) / 2a$

➔  $X_2 = (X_1^2 + a^2 + x_2^2 - 2a*x_1 + b^2) / 2b$

➔  $X_1^2 = 2a*x_1 - a^2 - x_2^2 + 2a*x_2 - b^2$

➔  $X_2^2 = 2a*x_1 - a^2 - x_1^2 + 2a*x_2 - b^2$

➔  $X_1, X_2, X_1^2$ , and  $X_2^2$  are all linearly separable from the rest of the features

Task 4: Recall that the equation of an ellipse in the 2-dimensional plane is  $c(x_1 - a)^2 + d(x_2 - b)^2 - 1 = 0$

Please show that an SVM using the polynomial kernel of degree 2,  $K(u, v) = (1 + u \cdot v)^2$ , is equivalent to a linear SVM in the feature space  $(1, x_1, x_2, x_1^2, x_2^2, x_1x_2)$  and hence that SVMs with this kernel can separate any elliptic region from the rest of the plane.

Used powerpoints and "The Kernel Trick in Support Vector Classification" as a reference.

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$$\bar{x}_i = [x_1 \ x_2] \text{ (original space)}$$

$$\text{Ellipse} \rightarrow c(x_1 - a)^2 + d(x_2 - b)^2 - 1 = 0$$

$$\Rightarrow c x_1^2 - 2ac x_1 + ca^2 + d x_2^2 - 2db x_2 + db^2 - 1 = 0$$

$$\begin{array}{ccccccc} \uparrow & \uparrow & \uparrow & \uparrow & \uparrow & \uparrow & \uparrow \\ \beta_3 & \beta_1 & \beta_0 & \beta_4 & \beta_2 & \beta_0 & \beta_0 \end{array}$$

$$\Rightarrow (ca^2 + db^2 - 1) + 2ac x_1 - 2db x_2 + c x_1^2 + d x_2^2 = 0$$

$$\Rightarrow \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1^2 + \beta_4 x_2^2 = 0$$

$$\Rightarrow \bar{x} = [1 \ x_1 \ x_2 \ x_1^2 \ x_2^2 \ x_1 x_2] \text{ (feature space)}$$

$$K(u, v) = (1 + u \cdot v)^2 = \left(1 + \begin{bmatrix} x_{i1} \\ x_{i2} \end{bmatrix} \begin{bmatrix} x_{j1} & x_{j2} \end{bmatrix}\right)^2$$

$$= (1 + (x_{i1} x_{j1}) + (x_{i2} x_{j2}))^2$$

$$= (1 + x_{i1}^2 x_{j1}^2 + x_{i2}^2 x_{j2}^2 + 2x_{i1} x_{j1} + 2x_{i2} x_{j2} + 2x_{i1} x_{i2} x_{j1} x_{j2})$$

$$= \begin{bmatrix} 1 & \sqrt{2} x_{i1} & \sqrt{2} x_{i2} & \sqrt{2} x_{i1} x_{i2} & x_{i1}^2 & x_{i2}^2 \end{bmatrix}^T \cdot \begin{bmatrix} 1 & \sqrt{2} x_{j1} & \sqrt{2} x_{j2} & \sqrt{2} x_{j1} x_{j2} & x_{j1}^2 & x_{j2}^2 \end{bmatrix}$$

$$= \boxed{\phi(x_i)^T \phi(x_j)} \text{ (in the feature space)}$$

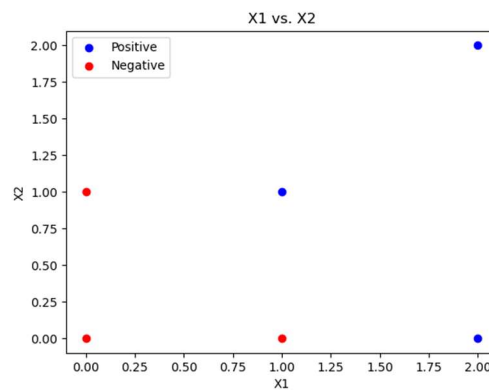
where  $\phi(x) = [1 \ \sqrt{2} x_1 \ \sqrt{2} x_2 \ \sqrt{2} x_1 x_2 \ x_1^2 \ x_2^2]$

$$\Rightarrow \text{SVM using } K(u, v) = (1 + u \cdot v)^2 \text{ is equivalent to an SVM in the described feature space}$$

**Task 5: Consider the following training data**

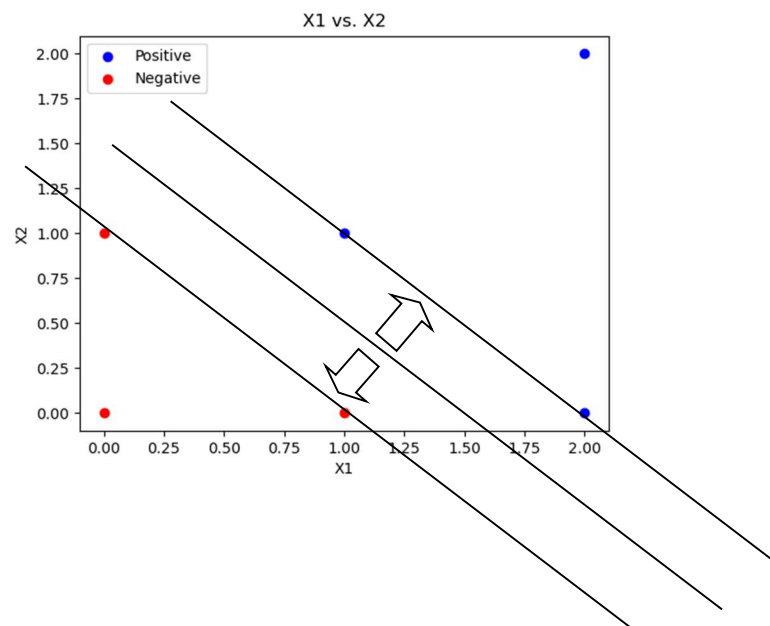
class	$x_1$	$x_2$
+	1	1
+	2	2
+	2	0
-	0	0
-	1	0
-	0	1

**(a) Plot these six training points. Are the classes  $\{+, -\}$  linearly separable?**



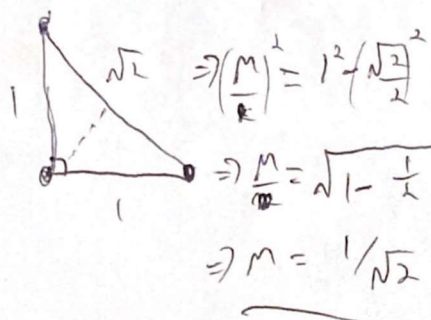
**From the above plot, it is clear that the classes are linearly separable, (by a line with negative slope and y-intercept  $\approx 1.5$ )**

**b) Construct the weight vector of the maximum margin hyperplane by inspection and identify the support vectors.**



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class	$x_1$	$x_2$
+	1	1
+	2	2
+	2	0
-	0	0
-	1	0
-	0	1



$\Rightarrow$  want to minimize  $\Phi(w) = \frac{1}{2} w^T w$  w/  $y_i(w x_i + b) \geq 1$

where  $\bar{w} = [\beta_1 \ \beta_2]$

support vectors are

$$s_1 = [0 \ 1] \ , \ s_2 = [1 \ 0] \quad (-1)$$

$$s_3 = [1 \ 1] \ , \ s_4 = [2 \ 0] \quad (+1)$$

$$\Rightarrow M = \frac{2}{|w|} \Rightarrow M^2 = \frac{4}{w^T w} \Rightarrow w^T w = \frac{4}{M^2}$$

$$M = \frac{1}{\sqrt{2}} \Rightarrow w^T w = \frac{4}{\left(\frac{1}{\sqrt{2}}\right)^2} = 8 = [\beta_1 \ \beta_2] \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix}$$

$$\Rightarrow \beta_1^2 + \beta_2^2 = 8 \Rightarrow \boxed{\beta_1 = \pm \sqrt{8 - \beta_2^2}}$$

Support vectors are those data points that define the hard margin. In this case there are 4:

$S_1 = \{0, 1\} (-)$ ,  $S_2 = \{1, 0\} (-)$ ,  $S_3 = \{1, 1\} (+)$ ,  $S_4 = \{2, 0\}$ .

There is also a margin of  $1/(\sqrt{2})$  in this case.

**Task 6: Consider a dataset with 3 points in 1-D:**

(class)	$x$
+	0
-	-1
-	+1

**(a) Are the classes  $\{+, -\}$  linearly separable?**

**The classes are not linearly separable, as the + class is between two points in the - class on the x-axis**

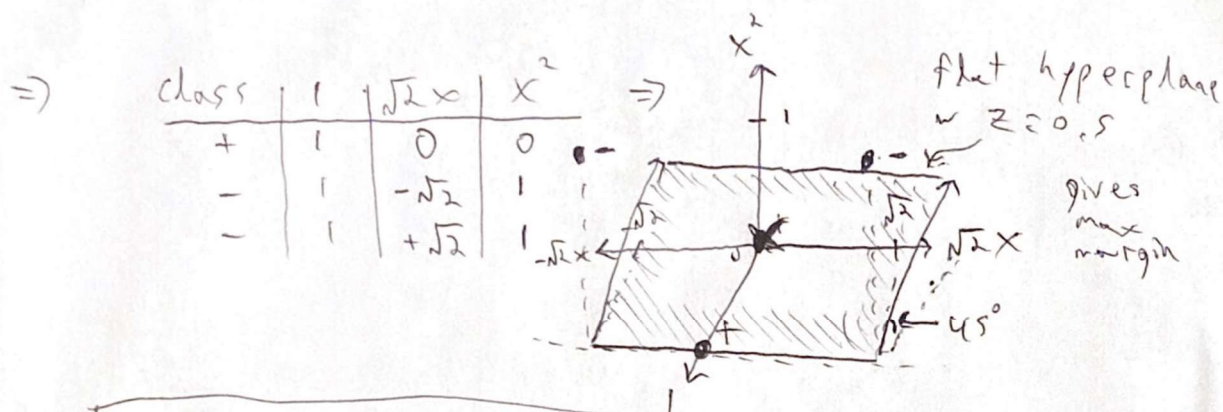
**(b) Consider mapping each point to 3-D using new feature vectors  $\phi(x) = [1, \sqrt{2}x, x^2]$ . Are the classes now linearly separable? If so, find a separating hyperplane.**

**See next page for work...**



6b)

let  $\phi(x) = [1 \quad \sqrt{2}x \quad x^2]$



$\Rightarrow$  By inspection, classes (+ and -) are linearly separable using  $\phi(x) = [1 \quad \sqrt{2}x \quad x^2]$

$\Rightarrow$  They are all support vectors,

$\Rightarrow$  let  $\beta_0 + \beta_1(\sqrt{2}x) + \beta_2 x^2 = 0$  be the separating hyperplane

$\Rightarrow \vec{w} = [\beta_0 \quad \beta_1 \quad \beta_2] \Rightarrow \text{minimize } \phi(w) = \frac{\beta_0^2 + \beta_1^2 + \beta_2^2}{2}$

$\Rightarrow$  separating hyperplane (w/ max margin) by inspection is:

(in feature space)  $\Rightarrow \boxed{(x^2) - 0.5 = 0}$

$\uparrow$   
 $z$

with margin  $\boxed{M=1}$

**Task 7: Learning SVMs on the Titanic dataset. Please report your five-fold cross validation classification accuracies on Titanic training set, with respect to the linear, quadratic, and RBF kernels. Which kernel is the best in your cases?**

Linear Kernel Accuracy (5-fold): 0.671156  
Quadratic Kernel Accuracy (5-fold): 0.672278  
RBF Kernel Accuracy (5-fold): 0.705948

In this case, the RBF kernel performed the best (~70% accuracy)  
See code for reference.

**GITHUB LINK:**

**<https://github.com/malleyconnor/cap5610/tree/master/hw4>**