

1.

Consider the dataset consisting of points  $(x, y)$ , where  $x$  is a real value, and  $y \in \{-1, 1\}$  is the class label. Let' us start with three points  $(x_1, y_1) = (-1, -1)$ ,  $(x_2, y_2) = (1, -1)$ ,  $(x_3, y_3) = (0, 1)$ . [By Hae Jin Song]

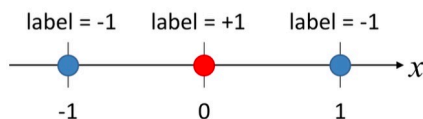


Figure 1: Three data points considered in this problem

- (a) Can three points shown in Figure 1, in their current one-dimensional feature space, be perfectly separated with a linear classifier? Explain why or why not.

- (b) Now we define a simple feature mapping  $\phi(x) = [x, x^2]^T$  to transform the three points from one- to two-dimensional feature space. Plot the transformed points in the new two-dimensional feature space.

Is there a linear decision boundary that can separate the points in this new feature space? Explain why or why not.

- (c) Given the feature mapping  $\phi(x) = [x, x^2]^T$ , write down the kernel function  $k(x, x')$ .

## 2.

We have trained a support vector machine with Laplace kernel determined by  $K(\mathbf{x}, \mathbf{x}_i) = \exp(-\|\mathbf{x} - \mathbf{x}_i\|_2)$ . The support vectors are  $\mathbf{x}_1^T = [2 \ 1 \ 0]$ ,  $\mathbf{x}_2^T = [-1 \ 1 \ 0]$ ,  $\mathbf{x}_3^T = [-5 \ 0 \ 0]$ , whose corresponding  $\alpha_i$ 's are  $\alpha_1 = -2$ ,  $\alpha_2 = 3$ ,  $\alpha_3 = -1$ . Also,  $\beta_0 = 1$ . As a reminder, the discriminant function of a SVM can be written in terms of the  $\alpha_i$ 's and  $\beta_0$ . Determine the class to which the test vector  $\mathbf{x}^T = [0 \ 0 \ 0]$  is classified.

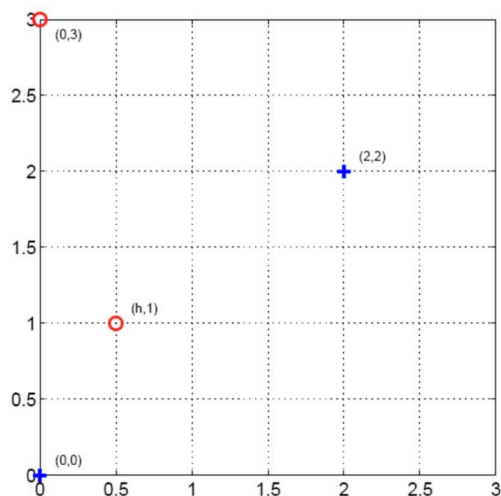
# 3.

Consider the following data set: In class 1, we have  $[1 \ 1]^T, [1 \ 2]^T, [2 \ 2]^T$ . In class 2, we have  $[1.5 \ 1.5]^T$ .

- (a) Sketch the data set and determine whether or not it is linearly separable.
- (b) Regardless of the answer to 2a, find a quadratic feature  $X_3 = f(X_1, X_2) = aX_1^2 + bX_2^2 + cX_1X_2 + dX_1 + eX_2 + f$ , that makes the data linearly separable; that is,  $X_3 \geq 0$  for members of class 1, and  $X_3 < 0$  for members of class 2. Find the maximum margin classifier only based on  $X_3$ . Hint: The equation of the maximum margin classifier based on only one feature is  $X_3 = \beta_0$  and you should determine  $\beta_0$ .
- (c) By solving  $X_3 = f(X_1, X_2) = \beta_0$  for  $X_2$ , find the equation of the decision boundary in the original feature space and sketch it. Show the regions in the feature space that are classified as class 1 and class 2. You do not need to be very precise.

# 4.

3. Suppose we only have four training observations in two dimensions:



positive examples are  $\mathbf{x}_1 = [0 \ 0]^T$ ,  $\mathbf{x}_2 = [2 \ 2]^T$  and negative examples are  $\mathbf{x}_3 = [h \ 1]^T$ ,  $\mathbf{x}_4 = [0 \ 3]^T$ .  $h$  is a parameter.

- What is the largest value of  $h$  for which the training data are still linearly separable?
- Determine the support vectors when  $h = 0.5$ .
- When the training points are separable, does the slope of the maximum margin classifier change? Why?
- Assume that  $h = .5$  and we have unlabeled data  $\mathbf{x}_5 = [3 \ 3]^T$ ,  $\mathbf{x}_6 = [2 \ 0.5]^T$ ,  $\mathbf{x}_7 = [1 \ 1.5]^T$ ,  $\mathbf{x}_8 = [2.5 \ 1.5]^T$ . Which one will be labeled first, if we are performing self-training? Which one will be labeled first, if we are performing active learning?

# 5.

We wish to classify the following two dimensional dataset using a Maximum Margin Classifier:

$$\left\{ \mathbf{x}_1 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \mathbf{x}_2 = \begin{bmatrix} -1 \\ 0 \end{bmatrix} \right\}, \text{ with } y = 1 \text{ and } \left\{ \mathbf{x}_3 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \mathbf{x}_4 = \begin{bmatrix} 0 \\ -1 \end{bmatrix} \right\} \text{ with } y = -1.$$

- (a) Determine the equation of the linear decision boundary  $f(\mathbf{x}) = \beta_0 + \beta_1 x_1 + \beta_2 x_2$ .
- (b) Determine the set of support vectors  $\mathcal{S}$ .

Hint: you do not need to solve an optimization problem to answer this question.

# 6.

Consider a dataset with 3 points in 1-D:

Index	$X$	$Y$
1	0	+
2	-1	-
3	+1	-

- (a) Carefully sketch these three training points. Are the classes linearly separable?
- (b) Consider mapping each point to 2-D using new feature vectors  $\boldsymbol{\varphi}(x) = [u_1(x), u_2(x)]^T$ , in which  $u_1(x)$  and  $u_2(x)$  are polynomial functions of  $x$ . Find a  $\boldsymbol{\varphi}(x)$  such that data are linearly separable in the new feature space.
- (c) The maximum margin classifier in the new space has the equation  $\mathbf{w}^T \boldsymbol{\varphi}(x) + b = 0$ . Find  $\mathbf{w}$  and  $b$ . Determine the decision boundary in the original 1-D space and the class assigned to  $x = \frac{1}{3}$  by the classifier.

# 7.

Consider the XOR classification problem (25 pts):

Index	$X_1$	$X_2$	$Y$
1	-1	-1	-1
2	-1	1	1
3	1	-1	1
4	1	1	-1

- (a) Find a single feature  $Z = f(X_1, X_2)$  that is a quadratic function and makes the data linearly separable. Find the maximum margin classifier using this single feature and project its decision boundary back onto the  $(X_1, X_2)$  space and sketch the decision boundary in this space.
- (b) Show that adding adding the feature  $X_3 = |X_1 - X_2|$  makes the data linearly separable. Find the maximum margin classifier in the space  $(X_1, X_2, X_3)$  for this data set and project it back onto  $(X_1, X_2)$  and sketch the decision boundary in this space.

# 8.

Consider the following data set (25 pts).

Index	$X_1$	$X_2$	$Y$
1	-2	0	Cross
2	-1	-1	Circle
3	-3	0	Cross
4	5	-2	Circle
5	0	-1	Circle
6	0.5	4	Cross
7	1	0	Circle
8	0	2	Cross

- (a) Sketch or plot the data.
- (b) Sketch or plot the maximum margin classifier and the margins.
- (c) Find the equation of the maximum margin classifier and those of the margins.
- (d) Provide the decision rule: If  $\beta_0 + \beta_1 X_1 + \beta_2 X_2 > 0$ , classify to ..., otherwise, classify to ....
- (e) Remove Observations 1,7. Does the equation of the separating hyperplane change?
- (f) Write the equation of the separating hyperplane in 2e as  $f(\mathbf{x}) = \sum_{i \in \mathcal{S}} \alpha_i \langle \mathbf{x}, \mathbf{x}_i \rangle + \beta_0$  and determine  $\alpha_i$ 's.