

# Machine learning Homework- Soft-Margin SVM and Kernels

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## Problem 1:

No it will not be the correct label. The training sample depends on the distance from the hyperplane decision boundary  $\xi$ . If  $\xi < 1$  for the training sample it gets classified correctly else it gets mis-classified.

## Problem 2:

The cost function for soft-margin SVM is

$$\min f_0(\mathbf{w}, b, \xi) = \frac{1}{2} \mathbf{w}^T \mathbf{w} + C \sum_{i=1}^N \xi_i \quad (1)$$

C is a penalizing factor on  $\xi$ .

case 1: when  $C = 0$  there is no restriction on  $\xi$  values.

case 2: when  $C \neq 0$  it encourages higher values of  $\xi$  and hence encouraging mis-classification.

## Problem 3:

## Problem 4:

## Problem 5:

1. from  $g(\alpha)$  we know that  $\alpha Q \alpha^T$  is equivalent to  $-\sum_{i=1}^N \sum_{j=1}^N y_i y_j \alpha_i \alpha_j \mathbf{x}_i \mathbf{x}_j$ . By rearranging the scalars we get,  $-\sum_{i=1}^N \sum_{j=1}^N \alpha_i y_i y_j \mathbf{x}_i \mathbf{x}_j \alpha_j$ .  
Therefore  $Q = (-yy^T (\text{hadamard}) XX^T)$
2. We know that  $Q = -p^T p$  and also we know that  $p^T p$  is positive semi definite due to its symmetric nature. So  $a^t(p^T p)a \geq 0$  but we negative sign also. Therefore,  $Q$  is negative semi definite.
3. The negative semi definiteness allows the concave optimisation to be a maximisation problem.