Machine learning Homework- Soft-Margin SVM and Kernels

Abinav Ravi Venkatakrishnan - 03694216 and Abhijeet Parida - 03679676

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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 ξ. 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

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

C is a penalizing factor on ξ.
case 1: when C = 0 there is no restriction on ξ values.
case 2: when C ¡ 0 it encourages higher values of ξ and hence encouraging mis-classification.

Problem 3:

Problem 4:

As we use KKT conditions for finding the minima of the contraint optimisation problem. Therefore, We staisfy the Slater theorem, which states if the constraint functions are affine, the duality gap is zero.

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 $Q = (-yy^T(hadamard)XX^T)$
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.