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 ξ. If $\xi < 1$ for the training sample it gets classified correctly else it gets mis-classified.

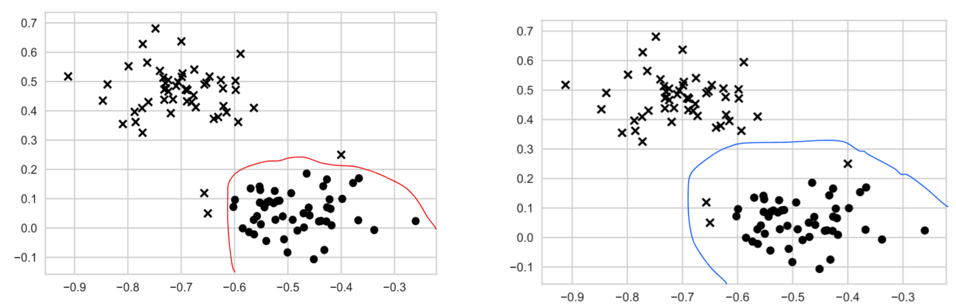
Problem 2:

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:



(a) $C = 10^{10}$ (b) $C = 10^{-10}$

(a) (b)

Figure 1

The first case tends to have hard margin of SVM since the C value is very big and C tends to ∞. The second figure on the right has soft margin since the C value is very less and this can take some mis-classification.

Problem 4:

We know that $\sum_{i=0}^{N} a_i({x_i}^T x_j)^i$ is a polynomial kernel. by the kernel preserving operation we know that sum of valid kernel is also a valid kernel and hence $k(x1, x2)$

Problem 5:

Problem 6:

a) The algorithm is trying to find the matching characters in the given string.
b) The alphabets are mapped from SxS space to real space. The real number is actually a mapping of s$\geq$0 which

means that the Mercer Matrix has values which are positive or zero i.e. the matrix is Positive semi-definite thereby making the Kernel valid.

Problem 7:

For linearly separated points the SVM is given by

$$y_i(w^T\phi(x_i) + b) > 0 \tag{2}$$

this equation is transformed into a different forms by using the kernel trick for non linear separations. But this is possible when the limit of σ tends to zero or very low values of σ