

Machine learning Homework- Soft-Margin SVM and Kernels

Abinav Ravi Venkatakrishnan - 03694216 and Abhijeet Parida - 03679676

December 9, 2018

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

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

C is a penalizing factor on ξ .

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

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

Problem 3:

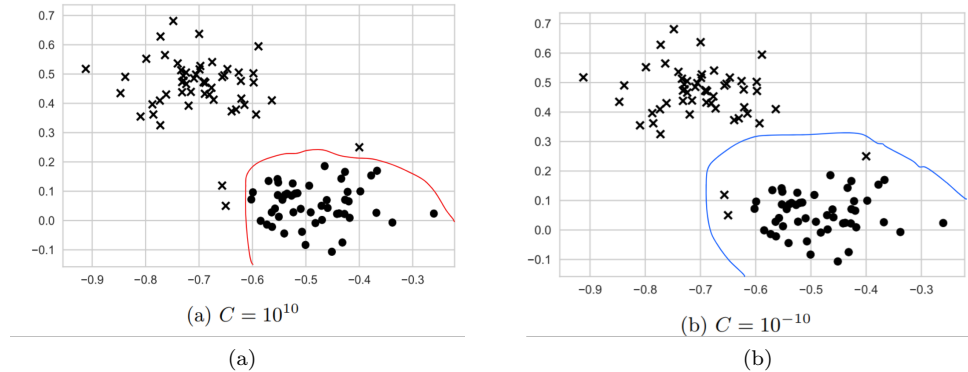


Figure 1

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 $k(x_1, x_2)$

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

$$y_i(w^T \phi(x_i) + b) > 0 \quad (2)$$

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