

Problem Set 3*

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Problem 1

Given the dual formulation of the SVM problem:

$$\max_{\alpha} \left(\sum_{i=1}^N \alpha_i - \frac{1}{2} \sum_{i,j=1}^N \alpha_i \alpha_j y_i y_j K(x_i, x_j) \right) \quad (1)$$

subject to the constraints

$$0 \leq \alpha_i \leq C, \quad \text{and} \quad \sum_{i=1}^N \alpha_i y_i = 0. \quad (2)$$

We can define the following to transform it into the canonical form of a quadratic program:
The objective vector v is:

$$v = -1_N, \quad (3)$$

where 1_N is an N -dimensional vector of ones.

The Hessian matrix H is:

$$H_{ij} = y_i y_j K(x_i, x_j), \quad (4)$$

which is an $N \times N$ symmetric matrix.

The inequality constraints matrix A and vector a are:

$$A = \begin{pmatrix} I_N \\ -I_N \end{pmatrix}, \quad a = \begin{pmatrix} C_N \\ 0_N \end{pmatrix}, \quad (5)$$

where I_N is the $N \times N$ identity matrix, C_N is an N -dimensional vector with all elements equal to C , and 0_N is an N -dimensional vector of zeros.

The equality constraints matrix B and vector b are:

$$B = 1_N^T y, \quad b = 0, \quad (6)$$

where y is the vector of labels y_i .

The solution u^* of the quadratic program:

$$\min_u \left(\frac{1}{2} u^T H u + v^T u \right) \quad (7)$$

subject to

$$A u \leq a, \quad B u = b \quad (8)$$

will be equivalent to the solution α^* in the SVM dual problem.

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Problem 2

Given a solved Support Vector Machine (SVM) dual problem with α^* obtained, the bias term b^* can be computed as follows.

For any support vector x_k with $0 < \alpha_k^* < C$, the following condition holds:

$$y_k(\langle w^*, \phi(x_k) \rangle + b^*) = 1. \quad (9)$$

By substituting the expression for $w^* = \sum_{i=1}^N \alpha_i^* y_i \phi(x_i)$, we get:

$$y_k \left(\sum_{i=1}^N \alpha_i^* y_i \langle \phi(x_i), \phi(x_k) \rangle + b^* \right) = 1. \quad (10)$$

Given that $K(x_i, x_k) = \langle \phi(x_i), \phi(x_k) \rangle$, it simplifies to:

$$y_k \left(\sum_{i=1}^N \alpha_i^* y_i K(x_i, x_k) + b^* \right) = 1. \quad (11)$$

Solving for b^* gives us the exact formula:

$$b^* = y_k - \sum_{i=1}^N \alpha_i^* y_i K(x_i, x_k). \quad (12)$$

This formula can be used to compute b^* using any support vector x_k .