

Duality Formulaton of Max-Margin Classifier*

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Abstract

In this fake-paper I write a short mathematical explication of how to formulate the Max-Margin classifier in it's dual form. I go through it step by step.

1 Primal formulation

To be written ...

2 Lagrangian function

There will be as always 3 kinds of terms, coming from either the *the objective function*, *a constraint* or *a variable constraint*.

$$L(w, b, \xi, \mu, \nu) = \frac{1}{2} ||w||_2^2 + \sum_{i=1}^n C\xi_i + \mu_i(y_i b + 1 - y_i w^T x_i - \xi_i) - \nu_i \xi_i \quad (1)$$

We now derivativs for each variable-type and get an equation. There are 3 'types' of variables here, so we will get 3 equations.

2.1 Derivative with respect to w

$$\frac{dL}{dw} = 0 = w - \sum_{i=1}^n \mu_i y_i x_i \quad (2)$$

Here x_i means the sum of the values in the **vector** x_i .

2.2 Derivative with respect to b

$$\frac{dL}{db} = 0 = \sum_{i=1}^n \mu_i y_i \quad (3)$$

*This is the first time I use latex

2.3 Derivative with respect to ξ

$$\frac{dL}{db} = 0 = C - \mu_i - \nu_i \quad (4)$$

3 Reducing the lagrangian by substitution

First we substitute (4) which is clearly eliminating the ξ terms.

$$L(w, b, \mu) = \frac{1}{2} \|w\|_2^2 + \sum_{i=1}^n \mu_i (y_i b + 1 - y_i w^T x_i) \quad (5)$$

Let's rewrite the function using $\|w\|_2^2 = w^T w$

$$L(w, b, \mu) = w^T \left(\frac{1}{2} w - \sum_{i=1}^n \mu_i y_i x_i \right) + \sum_{i=1}^n \mu_i (y_i b + 1) \quad (6)$$