

# 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

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

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\*This is the first time I use latex

### 2.3 Derivative with respect to $\xi$

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

## 3 Reducing the lagrangian by substitution

First we substitute (4) which is clearly eliminating the  $\xi$  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  $\|w\|_2^2 = w^T w$  and other simple rewritings.

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