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# Week 2 Report

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## Abstract

Support Vector Machine is used to classify. It finds a best line to separate two sets. When it's difficult to do so, we can allow small errors or map the vectors to higher dimensions.

## 1 Original Problem

Given two sets of points, we want to find a line to classify them i.e. to draw a line between the two sets whose distance to the nearest point is as far as possible. Mathematically, we want a function  $f(x) = \text{sgn}(\omega^T x + b)$  which returns 1 for one set and -1 for the other. In addition, we want to maximize  $\gamma$ , s.t.  $\frac{1}{\|\omega\|} y^{(i)} (\omega^T x^{(i)} + b) \geq \gamma, i = 1, \dots, m$ .

After transformation, we equivalently need to minimize  $\frac{1}{2} \|\omega\|^2$ , s.t.  $y^{(i)} (\omega^T x^{(i)} + b) \geq 1, i = 1, \dots, m$ . Then we only need to find a mathematician to solve this Lagrangian problem.

## 2 Improvements

There are times when the two sets are not linearly separable.

### 2.1 Allowing Errors

If the two sets intersect a bit, we can allow an error  $\xi_i$  and define a punishment constant  $C$ . Then the problem becomes to minimize  $\frac{1}{2} \|\omega\|^2 + C \sum_i \xi_i$ , s.t.  $y^{(i)} (\omega^T x^{(i)} + b) \geq 1 - \xi_i$ .

### 2.2 Kernel Function

With a proper function, we can transform  $x$  to a higher dimension so that the classification becomes easy. That is, we substitute all the  $x$  with  $\Phi(x)$  where  $\Phi$  is a mapping function.

Moreover, in the original problem, the  $\omega$  we want can actually be expressed in the form of  $w = \sum_i \alpha_i y_i x_i$  and we only need to find out the best  $\alpha_i$ . Notice that  $\omega^T x + b = \sum_i \alpha_i y_i \langle x^{(i)}, x \rangle + b$ , so we only need to redefine the inner product. In fact,  $x_i$  doesn't even have to be a vector as long as you can define a positive-definite inner product.

## 3 Training the SVM

Firstly we define the kernel function  $K(x, y)$  and punishment constant  $C$ . Then we can use a QP solver to directly calculate the  $\alpha_i$  we want, but this approach is too slow. Instead, we introduce SMO (sequential minimal optimization) algorithm. We repeat until converge randomly choosing a pair  $\alpha_i$  and  $\alpha_j$  and optimize the target function while holding the other  $\alpha$ s.