

# Notes - October 25

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## 1 Hard-Margin Support Vector Machine

Linear decision rule:

$$\begin{aligned} \mathbf{w}^T \mathbf{x} + b &> 0 && \Rightarrow 1 \\ \mathbf{w}^T \mathbf{x} + b &< 0 && \Rightarrow 0 \end{aligned}$$

We solve for an optimal  $\mathbf{w}$  and  $b$  by doing

$$\min_{\mathbf{w}, b} \frac{1}{2} \mathbf{w}^T \mathbf{w} \quad : \quad y_i (\mathbf{w}^T \mathbf{x}_i + b) \geq 1 \forall i$$

QP-solvers (Quadratic Problem Solvers) solve equations of the form

$$\min_z \frac{1}{2} \mathbf{z}^T \mathbf{P} \mathbf{z} + \mathbf{q}^T \mathbf{z} \quad : \quad \mathbf{G} \mathbf{z} \leq \mathbf{h}, \mathbf{A} \mathbf{z} = \mathbf{b}, \text{etc..}$$

Obviously using a QP-solver will help us find an optimal  $\mathbf{w}$ ,  $b$ , so we need not implement this ourselves.

Notice that

$$\begin{bmatrix} w_0 & w_1 & b \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} w_0 \\ w_1 \\ b \end{bmatrix} = \begin{bmatrix} w_0 \\ w_1 \\ 0 \end{bmatrix} \begin{bmatrix} w_0 \\ w_1 \\ b \end{bmatrix} = \mathbf{w}^T \mathbf{w}$$

So we let  $\mathbf{P} = \begin{bmatrix} I_d & 0 \\ 0 & 0 \end{bmatrix}_{d+1 \times d+1}$  in order to satisfy our needs.

$$y_i \mathbf{w}^T \mathbf{x}_i + y_i b \geq 1$$

$$\Rightarrow \begin{bmatrix} y_1 \mathbf{x}_1^T y_1 \\ y_2 \mathbf{x}_2^T y_2 \\ \vdots \\ y_n \mathbf{x}_n^T y_n \end{bmatrix} \begin{bmatrix} w \\ b \end{bmatrix} \geq \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

So what we just looked at was the “Hard-Margin SVM Primal”, but there is a more complicated version called the “Hard-Margin SVM Dual”. However, they both end up being quadratic programs with linear constraints.

Notice the following:

- The optimal weight vector is a linear combination of only a few of our training examples

$$\mathbf{w}^* = \sum_i \alpha_i^* y_i \mathbf{x}_i$$

- Both the objective and classifying new examples are just based on dot-products between input vectors.

Two opposing goals

- Very large margin, many errors.
- Very small margin, few errors.

This yields a hyperparameter that we may find ourselves tweaking in homework at some point. Let’s allow each example to violate our requirement by some value. That is,

$$y_i \mathbf{w}^T \mathbf{x}_i + y_i b \geq 1 + \eta$$

Where  $\eta$  is our error or “slack variable”.