

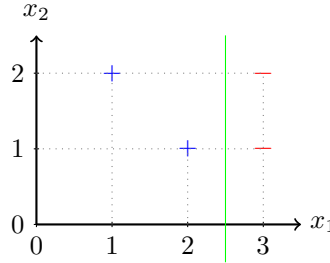
# CS680, Spring 2020, Assignment 4

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## Exercise 1

1. The optimal solution should maximize the minimum distance from data points to the hyperplane. In this problem the data points are 2d and therefore the solution should be a line separate two classes of points. Suppose the two dimension are  $x_1$  and  $x_2$ . The closest positive and negative points are (2,1) and (3,1), thus, the optimal solution is the line which perpendicular to the line connected (2,1) and (3,1),  $x_1 = 2.5$ . Hence,  $\mathbf{w}^* = [-1, 0]^T, b^* = 2.5$



2. Use the slack variables  $\xi$ , we can formulate the optimization problem as

$$\begin{aligned} \min_{\mathbf{w}, b, \xi} \quad & \frac{1}{2} \|\mathbf{w}\|_2^2 + C \sum_{i=1}^n \xi_i^2 \\ \text{s.t.} \quad & 1 - y_i(\mathbf{w}^T \mathbf{x}_i + b) \leq \xi_i, i = 1, 2, \dots, n \end{aligned} \quad (1)$$

Then the Lagrangian is

$$\min_{\mathbf{w}, b, \xi} \max_{\alpha \geq 0} \frac{1}{2} \|\mathbf{w}\|_2^2 + \sum_{i=1}^n C \xi_i^2 + \alpha_i (1 - \xi_i - y_i(\mathbf{w}^T \mathbf{x}_i + b)) \quad (2)$$

Take the derivative of Lagrangian, and let them equal to zero, we can obtain

$$\begin{aligned} \frac{\partial}{\partial \xi_i} \quad & 2C\xi_i - \alpha_i = 0 \Rightarrow \xi_i = \frac{1}{2C} \alpha_i \\ \frac{\partial}{\partial \mathbf{w}} \quad & \mathbf{w} - \sum_{i=1}^n \alpha_i y_i \mathbf{x}_i = 0 \Rightarrow \mathbf{w} = \sum_{i=1}^n \alpha_i y_i \mathbf{x}_i \\ \frac{\partial}{\partial b} \quad & \sum_{i=1}^n \alpha_i y_i = 0 \end{aligned} \quad (3)$$

Put these back into the Lagrangian, we can obtain

$$\begin{aligned} & \frac{1}{2} \|\mathbf{w}\|_2^2 + \sum_{i=1}^n C \xi_i^2 + \alpha_i (1 - \xi_i - y_i(\mathbf{w}^T \mathbf{x}_i + b)) \\ & \frac{1}{2} \left\| \sum_{i=1}^n \alpha_i y_i \mathbf{x}_i \right\|_2^2 + \sum_{i=1}^n \alpha_i + \sum_{i=1}^n \frac{1}{4C} \alpha_i^2 - \sum_{i=1}^n \frac{1}{2C} \alpha_i^2 - \sum_{i=1}^n \alpha_i y_i \left( \sum_{j=1}^n \alpha_j y_j \mathbf{x}_j \right)^T \mathbf{x}_i \\ & \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j y_i y_j \mathbf{x}_i^T \mathbf{x}_j - \frac{1}{4C} \sum_{i=1}^n \alpha_i^2 \end{aligned} \quad (4)$$

Finally we can get,

$$\begin{aligned} \max_{\alpha \geq 0} \quad & \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j y_i y_j \mathbf{x}_i^T \mathbf{x}_j - \frac{1}{4C} \sum_{i=1}^n \alpha_i^2 \\ \text{s.t.} \quad & \sum_{i=1}^n \alpha_i y_i = 0 \end{aligned} \quad (5)$$

3.

$$\begin{aligned} & \frac{\partial}{\partial \mathbf{w}} C \max\{1 - y_i(\mathbf{w}^T \mathbf{x}_i + b), 0\}^2 \\ & \begin{cases} \frac{\partial}{\partial \mathbf{w}} C(1 - y_i(\mathbf{w}^T \mathbf{x}_i + b))^2 & 1 - y_i(\mathbf{w}^T \mathbf{x}_i + b) > 0 \\ 0 & \text{otherwise} \end{cases} \end{aligned} \quad (6)$$

$$\begin{cases} -2C \cdot y_i(1 - y_i(\mathbf{w}^T \mathbf{x}_i + b)) \mathbf{x}_i & 1 - y_i(\mathbf{w}^T \mathbf{x}_i + b) > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{aligned} & \frac{\partial}{\partial b} C \max\{1 - y_i(\mathbf{w}^T \mathbf{x}_i + b), 0\}^2 \\ & \begin{cases} \frac{\partial}{\partial b} C(1 - y_i(\mathbf{w}^T \mathbf{x}_i + b))^2 & 1 - y_i(\mathbf{w}^T \mathbf{x}_i + b) > 0 \\ 0 & \text{otherwise} \end{cases} \\ & \begin{cases} -2C \cdot y_i(1 - y_i(\mathbf{w}^T \mathbf{x}_i + b)) & 1 - y_i(\mathbf{w}^T \mathbf{x}_i + b) > 0 \\ 0 & \text{otherwise} \end{cases} \end{aligned} \quad (7)$$

4. First expand the expression of (3) in the Problem.

$$\begin{aligned} & \frac{1}{2\eta} \|\mathbf{z} - \mathbf{w}\|_2^2 + \frac{1}{2} \|\mathbf{z}\|_2^2 \\ & \frac{1}{2\eta} ((\mathbf{z} - \mathbf{w})^T (\mathbf{z} - \mathbf{w})) + \frac{1}{2} \mathbf{z}^T \mathbf{z} \\ & \frac{1}{2\eta} (\mathbf{z}^T \mathbf{z} - \mathbf{w}^T \mathbf{z} - \mathbf{z}^T \mathbf{w} + \mathbf{w}^T \mathbf{w}) + \frac{1}{2} \mathbf{z}^T \mathbf{z} \end{aligned} \quad (8)$$

Take the derivative of above equation and let it go to zero.

$$\begin{aligned} \frac{1}{\eta} \mathbf{z} - \frac{1}{2\eta} \mathbf{w} - \frac{1}{2\eta} \mathbf{w} + \mathbf{z} &= 0 \\ \left(\frac{1}{\eta} + 1\right) \mathbf{z} &= \frac{1}{\eta} \mathbf{w} \\ \mathbf{z} &= \frac{1}{1 + \eta} \mathbf{w} \end{aligned} \quad (9)$$

Therefore,  $\mathbf{P}^\eta(\mathbf{w}) = \frac{1}{1 + \eta} \mathbf{w}$

5. cs680-asg4.py

6. When  $C$  equals to 100, step size  $\eta$  is 0.001, we can obtain  $\mathbf{w} = [-1.992000, -0.003962]^T$ ,  $b = 4.948301$ . Since we can multiply each term of  $\mathbf{w}^*$  and  $b^*$  in Question 1 with 2, we can find that the result is close to the optimal solution we've derived in Question 1.