

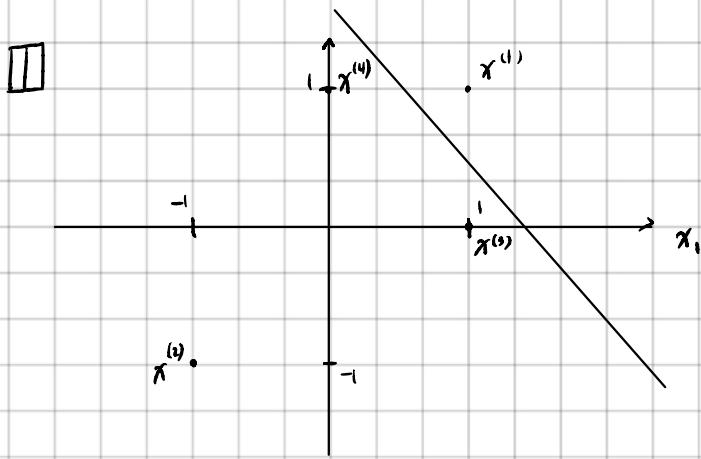
ECE421: Assignment #3

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Problem #1

Problem 1 The goal of this problem is to derive the parameters of a support vector machine with a hard margin. We will consider the following toy dataset of 4 points: $x^{(1)} = (1, 1)^\top$, $x^{(2)} = (-1, -1)^\top$, $x^{(3)} = (1, 0)^\top$, and $x^{(4)} = (0, 1)^\top$. $x^{(1)}$ is the only point from the positive class, whereas $x^{(2)}$, $x^{(3)}$, and $x^{(4)}$ are from the negative class. Put another way, $y^{(1)} = 1$ and $y^{(2)} = y^{(3)} = y^{(4)} = -1$.

1. (2 points) Plot the data and draw the maximum-margin hyperplane. By inspecting the plot, give the equation of this hyperplane. You will use it to verify your answers at the end of this problem.



line passes through both $(0.5, 1)^\top$ and $(1, 0.5)^\top$

$$x_2 = \left(\frac{0.5-1}{1-0.5}\right)x_1 + 1.5$$

$$x_2 = -x_1 + 1.5$$

$$x_1 + x_2 - 1.5 = 0$$

2. (1 point) Which of the points are support vectors?

2 Support vectors of the maximum margin hyperplane

are $x^{(1)} = (1, 1)^\top$, $x^{(3)} = (1, 0)^\top$, $x^{(4)} = (0, 1)^\top$

3. (1 point) Recall the optimization problem we defined for the SVM with a hard margin:

$$\min_{\vec{w}, b} \frac{1}{2} \|\vec{w}\|^2 \text{ s.t. } \forall j (\vec{w} \cdot x^{(j)} + b) y^{(j)} \geq 1 \quad (1)$$

Write down the Lagrangian $L(\vec{w}, b, \vec{\alpha})$ corresponding to this problem, where $\vec{\alpha}$ is the vector of dual variables.

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$$L(\vec{w}, b, \vec{\alpha}) = \frac{1}{2} \|\vec{w}\|^2 - \sum_j \alpha_j [(\vec{w} \cdot x^{(j)} + b) y^{(j)} - 1]$$

4. (2 points) We can therefore rewrite Equation 1 as follows:

$$\min_{\vec{w}, b} \max_{\vec{\alpha}} L(\vec{w}, b, \vec{\alpha})$$

Because Slater's condition holds, this is equivalent to solving:

$$\max_{\vec{\alpha}} \min_{\vec{w}, b} L(\vec{w}, b, \vec{\alpha}) \quad (2)$$

Given a fixed $\vec{\alpha}$, solve the inner (minimization) problem. You should obtain two relationships taking the form of

$$\begin{aligned} A &= \sum_j B_j C_j \vec{D}_j \\ \sum_j E_j F_j &= G \end{aligned}$$

4 From previous problem.

$$L(\vec{w}, b, \vec{\alpha}) = \frac{1}{2} \|\vec{w}\|^2 - \sum_j \alpha_j [(\vec{w} \cdot x^{(j)} + b) y^{(j)} - 1]$$

$$\max_{\vec{\alpha}} \min_{\vec{w}, b} L(\vec{w}, b, \vec{\alpha})$$

$$\frac{\partial L(\vec{w}, b, \vec{\alpha})}{\partial \vec{w}} = \vec{w} + \sum_j \alpha_j x^{(j)} y^{(j)} = 0$$

$$\underline{\vec{w}^* = \sum_j \alpha_j x^{(j)} y^{(j)}}$$

$$\frac{\partial L(\vec{w}, b, \vec{\alpha})}{\partial b} = \sum_j \alpha_j y^{(j)} = 0$$

$$\text{fixing } \vec{\alpha}, \text{ we get } \begin{cases} \vec{w}^* = \sum_j \alpha_j x^{(j)} y^{(j)} \\ \sum_j \alpha_j y^{(j)} = 0 \end{cases}$$

5. (2 points) Simplify Equation 2 with the result of question 4. Show that it takes the form of

$$\max_{\alpha} \sum_j A_j - \frac{1}{2} \sum_j \sum_k B_j C_k D_j E_k \vec{F} \cdot \vec{G}$$

[5]

$$\max_{\alpha} \min_{\vec{w}, b} L(\vec{w}, b, \alpha)$$

from previous questions we know that

$$L(\vec{w}, b, \alpha) = \frac{1}{2} \|\vec{w}\|^2 - \sum_j \alpha_j [(\vec{w} \cdot \vec{x}^{(j)} + b) y^{(j)} - 1]$$

$$\vec{w}^* = \sum_j \alpha_j \vec{x}^{(j)} y^{(j)} \quad (1)$$

$$\sum_j \alpha_j y^{(j)} = 0 \quad (2)$$

$$\max_{\alpha} L(\vec{w}, b, \alpha) = \max_{\alpha} \left(\frac{1}{2} \sum_j \sum_k \alpha_j \alpha_k y^{(j)} y^{(k)} \vec{x}^{(j)} \vec{x}^{(k)} \right)$$

$$- \sum_k \alpha_k \left(\left(\sum_j \alpha_j y^{(j)} \right) \vec{x}^{(k)} + b \right) y^{(k)} \\ + \sum_j \alpha_j$$

$$= \max_{\alpha} \left(\sum_j \alpha_j - \frac{1}{2} \sum_j \sum_k \alpha_j \alpha_k y^{(j)} y^{(k)} \vec{x}^{(j)} \vec{x}^{(k)} \right. \\ \left. - b \sum_j \alpha_j y^{(j)} \right)$$

0 → according to equation (2)

$$= \max_{\alpha} \left(\sum_j \alpha_j - \frac{1}{2} \sum_j \sum_k \alpha_j \alpha_k y^{(j)} y^{(k)} (\vec{x}^{(j)})^T \vec{x}^{(k)} \right)$$

6. (1 point) We now come back to our toy dataset. Because it has 4 training points, we have $j \in 1..4$, i.e., four dual variables. For points that are not support vectors, recall from class that the corresponding constraints in Equation 1 can be removed. Deduce the value of one of the dual variable α_j corresponding to one value of j (i.e., one constraint) which we will write j^* to not reveal the answer. Follow indexes introduced in the problem statement above when describing the dataset.

[6] for $j=2$ $\vec{x}^{(2)} = (-1, -1)^T$

it is not constrained from constraint where
 $j=2$.

$$\therefore \alpha_2 = 0$$

7. (1 point) Deduce from the second expression found in question 4 (i.e., $\sum_j E_j F_j = G$), a relationship between all remaining dual variables α_j for $j \neq j^*$

[7] from Question 4

$$\sum_j \alpha_j y^{(j)} = 0$$

$$\rightarrow \alpha_1 y^{(1)} + \alpha_2 y^{(2)} + \alpha_3 y^{(3)} + \alpha_4 y^{(4)}$$

$$= \alpha_1 - \alpha_2 - \alpha_3 - \alpha_4 = 0$$

$$\downarrow \alpha_2 = 0$$

$$= \alpha_1 - \alpha_3 - \alpha_4 = 0$$

8. (3 points) Solving the optimization problem from question 5, and using question 7 in addition, find values for all dual variables α_j for $j \in 1..4$.

[8]

$$\alpha_1, \alpha_3, \alpha_4 = \underset{\alpha_1, \alpha_3, \alpha_4}{\text{Max}} \left(\sum_{j=1}^4 \alpha_j - \frac{1}{2} \sum_{j=1}^4 \sum_{k=1}^4 \alpha_j \alpha_k y^{(j)} y^{(k)} (x^{(j)} \cdot x^{(k)}) \right)$$

compute pairwise dot product between training example.

$$x^{(1)\top} x^{(1)} = 2$$

$$x^{(1)\top} x^{(3)} = 1$$

$$x^{(1)\top} x^{(4)} = 1$$

$$x^{(3)\top} x^{(3)} = 1$$

$$x^{(3)\top} x^{(4)} = 0$$

$$x^{(4)\top} x^{(4)} = 1$$

$$x^{(1)} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, x^{(3)} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}, x^{(4)} = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$$

$$y^{(1)} = 1, y^{(3)} = y^{(4)} = -1$$

→ Expand $L(w^*, b^*, \alpha)$

$$\Rightarrow \underset{\alpha_1, \alpha_3, \alpha_4}{\text{Max}} -\frac{1}{2} \left(2\alpha_1^2 - \alpha_1 \alpha_3 - \alpha_1 \alpha_4 + \alpha_3^2 + \alpha_4^2 \right) + \alpha_1 + \alpha_3 + \alpha_4$$

we now have dual optimal problem.

$$\underset{\alpha_1, \alpha_3, \alpha_4}{\text{Max}} -\frac{1}{2} \left(2\alpha_1^2 - \alpha_1 \alpha_3 - \alpha_1 \alpha_4 + \alpha_3^2 + \alpha_4^2 \right) + \alpha_1 + \alpha_3 + \alpha_4$$

$$\alpha_1 - \alpha_3 - \alpha_4 = 0 \leftarrow \text{from previous question}$$

↓ Eliminate one variable

$$\alpha_4 = \alpha_1 - \alpha_3$$

$$\underset{\alpha_1, \alpha_3}{\text{Max}} -\frac{1}{2} \left(2\alpha_1^2 - \alpha_1 \alpha_3 - \alpha_1 (\alpha_1 - \alpha_3) + \alpha_3^2 + (\alpha_1 - \alpha_3)^2 \right) + \alpha_1 + \alpha_3 + (\alpha_1 - \alpha_3)$$

$$= \underset{\alpha_1, \alpha_3}{\text{Max}} -\frac{1}{2} \left(2\alpha_1^2 - \alpha_1^2 - \alpha_1 \alpha_3 + \alpha_1 \alpha_3 + \alpha_3^2 + \alpha_1^2 - 2\alpha_1 \alpha_3 + \alpha_3^2 \right) + 2\alpha_1$$

$$= \underset{\alpha_1, \alpha_3}{\text{Max}} -\frac{1}{2} \left(2\alpha_1^2 - 2\alpha_1 \alpha_3 + 2\alpha_3^2 \right) + 2\alpha_1$$

Substitute (***) into (**)

$$-2(2\alpha_1) + \alpha_3 + 2 = 0$$

$$-3\alpha_3 = -2$$

$$\alpha_3 = \frac{2}{3}$$

Substitute this result to (***)

$$\alpha_1 = 2 \left(\frac{2}{3} \right) = \frac{4}{3}$$

$$\alpha_4 = \alpha_1 - \alpha_3 = \frac{2}{3} = \alpha_3$$

9. (1 point) Deduce the numerical values of the two components of \vec{w} .

$$[9] \quad w^* = \sum_{i=1}^4 \alpha_i y_i x^{(i)}$$

$$w^* = \frac{4}{3}(1) \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \frac{2}{3}(-1) \begin{bmatrix} 1 \\ 0 \end{bmatrix} + \frac{2}{3}(-1) \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$= \begin{bmatrix} \frac{4}{3} - \frac{2}{3} \\ \frac{2}{3} \end{bmatrix} = \begin{bmatrix} \frac{2}{3} \\ \frac{2}{3} \end{bmatrix}$$

10. (2 points) Through an analysis of constraints in Equation 1 which are tight, deduce the numerical value of b . Hint: recall the role of support vectors here.

[10] bias can be computed from any support vectors

$$y^{(1)} (w^{(1)\top} x^{(1)} + b) = 1$$

$$b = 1 - (w^{(1)\top} x^{(1)}) = 1 - \left[\frac{2}{3} \frac{2}{3} \right] \begin{bmatrix} 1 \\ 1 \end{bmatrix} = 1 - \frac{4}{3} = -\frac{1}{3}$$

Compute partial derivative wrt α & set them to 0.

$$\frac{\partial L}{\partial \alpha_1} = -2\alpha_1 + \alpha_3 + 2 = 0 \quad (*)$$

$$\frac{\partial L}{\partial \alpha_3} = \alpha_1 - 2\alpha_3 = 0 \rightarrow \alpha_1 = 2\alpha_3 \quad (**)$$