

Homework - 9

COEN 240-Machine Learning

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Problem 1

Find the solution (x^*, y^*) to the following problem.

optimize xy

subject to $x + y = 10$

Sol:

Solution 1:

Standard form : xy

optimize xy

subject to $x+y-10=0$

Lagrangian : $L(x,y,\beta)$

$$= xy + \beta(x+y-10)$$

Partial derivative is

$$\nabla_x L(x,y,\beta) = y + \beta = 0 \rightarrow \text{Eq (1)}$$

$$\nabla_y L(x,y,\beta) = x + \beta = 0 \rightarrow \text{Eq (2)}$$

$$\nabla_\beta L(x,y,\beta) = x+y-10=0 \rightarrow \text{Eq (3)}$$

Now, we can solve for x, y is

from Eq (1) & Eq (2):

$$\Rightarrow \beta = -y \quad \text{--- (1)} \quad \text{and} \quad \beta = -x \quad \text{--- (2)}$$

now Equating (1) & (2)

$$\text{we get } -y = -x$$

$$\Rightarrow y = x.$$

So from Eq (3)

$$x+y-10=0$$

$$\Rightarrow 2x = 10$$

$$x = 5 \quad \text{or} \quad y = 5$$

$\therefore x^* = 5 \quad \text{and} \quad y^* = 5$

Problem 2

The SVM optimization can be defined by the primal form:

$$\begin{aligned} \min_{\mathbf{w}} \quad & \frac{1}{2} \|\mathbf{w}\|^2 \\ \text{subject to} \quad & y_i(\mathbf{w}^T \mathbf{x}_i + b) \geq 1, \quad i = 1, \dots, N \end{aligned}$$

Or by its dual form:

$$\begin{aligned} \max_{\alpha} J(\alpha) = \quad & \sum_{i=1}^N \alpha_i - \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j (\mathbf{x}_i^T \mathbf{x}_j) \\ \text{subject to} \quad & \alpha_i \geq 0, i = 1, \dots, N \text{ and } \sum_{i=1}^N \alpha_i y_i = 0 \end{aligned}$$

What is the Lagrangian function $L(\mathbf{w}, b, \alpha)$ evaluated at \mathbf{w} that minimizes that function?

Note this is the objective function $J(\alpha)$.

Hints:

1. Write the primal problem in standard form
2. Form the Lagrangian function $L(\mathbf{w}, b, \alpha)$
3. Find \mathbf{w} and b that minimize $L(\mathbf{w}, b, \alpha)$
4. Plug the results back into $L(\mathbf{w}, b, \alpha)$

Sol:

Solution 2:

step 1. First we write the primal problem in standard form:

$$\min_w \frac{1}{2} \|w\|^2 \text{ subject to } g_i(w) \\ = -y_i (w^T x_i + b) + 1 \leq 0$$

step 2. Second we form the Lagrangian function:

$$L(w, b, \alpha) \\ = \frac{1}{2} \|w\|^2 + \sum_{i=1}^N \alpha_i [-y_i (w^T x_i + b) + 1] \rightarrow \text{Eq(1)}$$

Here there is no β_i because there are no equality constraints.

step 3. Now we find w and b that minimize $L(w, b, \alpha)$

$$\nabla_w L(w, b, \alpha) = w - \sum_{i=1}^N \alpha_i y_i x_i = 0$$

$$w = \sum_{i=1}^N \alpha_i y_i x_i \rightarrow \text{Eq(2)}$$

$$\text{Now } \nabla_b L(w, b, \alpha) = \sum_{i=1}^N \alpha_i y_i = 0 \rightarrow \text{Eq(3)}$$

step 4: Now we plug in Eq(2) & Eq(3) into Eq(1)

$$L(w, b, \alpha) = \frac{1}{2} w^T w + \sum_{i=1}^N \alpha_i [-y_i (w^T x_i + b) + 1]$$

$$L(w, b, \alpha) = \frac{1}{2} \sum_{i=1}^N \alpha_i y_i x_i^T \cdot \sum_{j=1}^N \alpha_j y_j x_j$$

$$L(w, b, \alpha) = \frac{1}{2} \sum_{i=1}^N \alpha_i y_i x_i^T \cdot \sum_{j=1}^N \alpha_j y_j x_j + \sum_{i=1}^N \alpha_i \left[-y_i \left(\left(\sum_{j=1}^N \alpha_j y_j x_j^T \right) x_i + b \right) + 1 \right]$$

$$\Rightarrow L(w, b, \alpha) = \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j (x_i^T x_j) \\ - \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j (x_j^T x_i) - \sum_{i=1}^N \alpha_i y_i b + \sum_{i=1}^N \alpha_i$$

But,

$$\sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j (x_j^T x_i) = \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j (x_i^T x_j)$$

And from Eq (3) $\Rightarrow \sum_{i=1}^N \alpha_i y_i = 0$
 $\Rightarrow \sum_{i=1}^N \alpha_i y_i b = 0$

Therefore,

$$J(\alpha) = L(w, b, \alpha)$$

$$J(\alpha) = \sum_{i=1}^N \alpha_i - \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j (x_i^T x_j)$$

References:

1. Class notes:Support vector machines (SVMs)
2. <https://www.user.tu-berlin.de/mtoussai/teaching/13-Optimization/03-constrainedOpt.pdf>
3. <https://stats.stackexchange.com/questions/171676/models-for-machine-learning-constrained-optimization>
4. <https://georgian.io/constrained-optimization-how-to-do-more-with-less/>