

ASSIGNMENT-4

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3. The 5 fold cross validated accuracy is found to be 0.805.

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Q 1(a). Consider a ~~potential~~ potential solution to the above problem with some $\xi < 0$. Then the constraint $y^{(i)}(w^T x^{(i)} + w_0) \geq 1 - \xi_i$ would also be satisfied for $\xi_i = 0$, and the objective function would be lower, proving that this could be an optimal solution.

(b)
$$L(w, w_0, \xi, \alpha) = \frac{1}{2} w^T w + \frac{C}{2} \sum_{i=1}^n \xi_i^2 - \sum_{i=1}^m \alpha_i \left[y^{(i)} (w^T x^{(i)} + w_0) - 1 + \xi_i \right]$$

where $\alpha_i \geq 0$
for $i = 1 \dots m$.

(c) Now minimizing it by taking the gradient with respect to w , we get,

$$\nabla_w L = w - \sum_{i=1}^m \alpha_i y^{(i)} x^{(i)} = 0.$$

$$\Rightarrow w = \sum_{i=1}^m \alpha_i y^{(i)} x^{(i)}$$

Taking the derivative with respect to w_0 ,

$$\frac{\partial L}{\partial w_0} = - \sum_{i=1}^m \alpha_i y^{(i)} = 0.$$

$$0 = \sum_{i=1}^m \alpha_i y^{(i)}$$

Now for dual,

The objective function for the dual is

$$W(\alpha) = \min_{w, w_0, \xi} L(w, w_0, \xi, \alpha)$$

$$= \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n (\alpha_i y^{(i)} x^{(i)})^T (\alpha_j y^{(j)} x^{(j)})$$

$$+ \frac{1}{2} \sum_{i=1}^n \frac{\alpha_i}{\sum_{j=1}^n \alpha_j} \xi_i^2$$

$$- \sum_{i=1}^n \alpha_i \left[y^{(i)} \left(\left(\sum_{j=1}^n \alpha_j y^{(j)} x^{(j)} \right)^T x^{(i)} + w_0 \right) \right]$$

$$= -\frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j y^{(i)} y^{(j)} (x^{(i)})^T x^{(j)} - 1 + \xi_i$$

$$+ \frac{1}{2} \sum_{i=1}^n \alpha_i \xi_i - \left(\sum_{i=1}^n \alpha_i y^{(i)} \right) w_0 +$$

$$\sum_{i=1}^n \alpha_i - \sum_{i=1}^n \alpha_i \xi_i$$

$$= \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j y^{(i)} y^{(j)} (x^{(i)})^T x^{(j)}$$

$$- \frac{1}{2} \sum_{i=1}^n \alpha_i \xi_i$$

$$= \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j y^{(i)} y^{(j)} (x^{(i)})^T x^{(j)}$$

$$- \frac{1}{2} \sum_{i=1}^n \frac{\alpha_i^2}{C}$$

Then the dual formulation is:

$$\max_{\alpha} \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j y^{(i)} y^{(j)} (x^{(i)})^T x^{(j)}$$

$$- \frac{1}{2} \sum_{i=1}^n \frac{\alpha_i^2}{C}$$

$$\text{s.t. } \alpha_i \geq 0, \quad i = 1, \dots, n$$

$$\sum_{i=1}^n \alpha_i y^{(i)} = 0.$$

(d) To find w and w_0
using $\frac{\partial L}{\partial w} = 0$

$$\Rightarrow \bar{w} - \sum_{i=1}^n \alpha_i y_i \bar{x}_i = 0$$

$$\bar{w} = \sum_{i=1}^n \alpha_i y_i \bar{x}_i$$

using complementarity condition,

$$\alpha_i [y_i (\bar{w}^T \bar{x} + w_0) - 1] = 0.$$

$$\Rightarrow \alpha_i [y_i ((\sum_{i=1}^n \alpha_i y_i \bar{x}_i)^T \bar{x} + \bar{w}_0) - 1] = 0$$

$$\bar{w}_0 = \frac{1}{y_i} - (\sum_{i=1}^n \alpha_i y_i \bar{x}_i)^T \bar{x}.$$

Q.2

v-SVM

$$w^T x + w_0 = \pm \rho \text{ (Margin plane)}$$

$$\min f(w, w_0, \xi, \rho) = \frac{\|w\|^2}{2} - \nu \rho + \frac{1}{n} \sum_{i=1}^n \xi_i$$

where $0 \leq \nu \leq 1$.

$$\text{constraints } y_i [w^T x_i + w_0] \geq \rho + \xi_i \quad i=1(1)n$$

$$\xi_i \geq 0 \quad i=1(1)n$$

$$\rho \geq 0$$

(a) Lagrangian for the problem is:

$$L(w, w_0, \xi, \rho, \alpha, \beta, \delta) = \frac{1}{2} \|w\|^2 - \nu \rho$$

$$+ \frac{1}{n} \sum_{i=1}^n \xi_i - \sum_{i=1}^n (\alpha_i (y_i / w^T x_i + w_0) - \rho + \xi_i)$$

$$- \sum_{i=1}^n (\alpha_i (y_i / w^T x_i + w_0) - \rho + \xi_i)$$

$$+ \beta_i \xi_i - \delta \rho$$

where $\alpha_i, \beta_i, \delta \geq 0$ Now, this fn. has to minimize w.r.t w_i , w_0, ξ_i, ρ .

$$\frac{\partial L}{\partial w} = \nabla_w L = w - \sum_{i=1}^n \alpha_i y_i x_i = 0$$

$$\Rightarrow w = \sum_{i=1}^n \alpha_i y_i x_i \quad \text{--- (1)}$$

$$\frac{\partial L}{\partial w_0} = - \sum_{i=1}^n \alpha_i y_i = 0$$

$$\therefore \sum_{i=1}^n \alpha_i y_i = 0 \quad \text{--- (2)}$$

$$\frac{\partial L}{\partial \xi_i} = \frac{1}{n} - \alpha_i - \beta_i = 0$$

$$\Rightarrow \boxed{\alpha_i + \beta_i = \frac{1}{n}} \quad \text{--- (3)}$$

$$\frac{\partial L}{\partial \rho} = -\nu + \sum_{i=1}^n \alpha_i - \delta = 0$$

$$\Rightarrow \nu = \sum_{i=1}^n \alpha_i - \delta \quad \text{--- (4)}$$

Now substituting values, we have

$$\begin{aligned} w(\alpha, \beta, \delta) &= \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n (\alpha_i y_i x_i)^T (\alpha_j y_j x_j) \\ &\quad + \frac{1}{n} \sum_{i=1}^n \xi_i - \nu \rho - \sum_{i=1}^n \alpha_i \left[y_i \left(\left(\sum_{j=1}^n \alpha_j y_j x_j \right)^T x_i + \omega_0 \right) - \rho + \xi_i \right] - \delta \delta - \sum_{i=1}^n \beta_i \xi_i \\ &= -\frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j y_i y_j x_i^T x_j + \frac{1}{n} \sum_{i=1}^n \xi_i - \nu \rho \\ &\quad - \left(\sum_{i=1}^n \alpha_i y_i \right) \omega_0 + \sum_{i=1}^n \alpha_i \rho - \sum_{i=1}^n (\alpha_i + \beta_i) \xi_i \end{aligned}$$

$$\Rightarrow w(\alpha, \beta, \delta) = -\frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j y_i y_j x_i^T x_j$$

(b) The dual formulation is

$$\max_{\alpha, \beta, \delta} w(\alpha, \beta, \delta) = \max_{\alpha, \beta, \delta} -\frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j y_i y_j x_i^T x_j$$

$$\text{subject to } 0 \leq \alpha_i \leq \frac{1}{n}, \quad \sum_{i=1}^n \alpha_i \geq \nu.$$

Q3

(c) Now to calculate \bar{w} , we can use the optimal values from dual problem α_i^* &

$$\bar{w}^* = \sum_{i=1}^n \alpha_i^* y_i x_i$$

To find w_0^* , we use the complementarity slackness condition, of KKT

$$\alpha_i [(w^T x_i + w_0) y_i - \rho + \xi_i] = 0$$

$$\beta_i \xi_i = 0$$

$$w^T x + w_0 = \pm \rho$$

w_0^* & ρ can be found from these equations.

Q.4(a) $S \subseteq \mathbb{R}^n$ is a convex set.
Show that

$$\theta_1 \bar{x}_1 + \theta_2 \bar{x}_2 + \dots + \theta_k \bar{x}_k \in S, \text{ where } \bar{x}_i \in S, i=1, \dots, k \\ \& \sum_{i=1}^k \theta_i = 1.$$

We need to prove that S contains any convex combination of vectors $\bar{x}_i \in S$.

~~Let~~ let $y = \sum_{i=1}^m \theta_i \bar{x}_i$ $[\sum \theta_i = 1]$ — (A)

By applying induction on m ,
Base case: $m=1$.

In case $m=1$, $y = \bar{x}_1 \in S$ which is true ~~also~~ already.

Hypothesis: Assume that we know that any convex combination of $m-1$ vectors ($m \geq 2$) from S is present in S .

To prove: The above statement remains valid for convex combination of m vectors as well.

From (A),

y can be written as:

$$y = (1 - \theta_m) \sum_{i=1}^{m-1} \frac{\theta_i}{1 - \theta_m} \bar{x}_i + \theta_m \bar{x}_m.$$

Note that, θ_m can be assumed to be < 1 .

because $\sum \theta_i = 1$, & if $\theta_m = 1$.

then other $\theta_i = 1$ to $m-1 = 0$.

$$\therefore y = \bar{x}_m \in S$$

$$y = (1 - \theta_m)z + \theta_m x_m$$

with $z, x_m \in S$.

$\therefore y \in S$, [acc. to definition of convex set]
hence proved.

4(b). Show that the set,

$$S = \{x = (x_1, x_2) \in \mathbb{R}_+^2 \mid x_1, x_2 \geq 1\} \text{ is convex}$$

Consider a convex combination z of 2 points $x = (x_1, x_2)$ & $y = (y_1, y_2)$ belonging to the set S .

Case 1: if $x \geq y$, then,

$$z = \theta x + (1-\theta)y \geq y \\ \& z_1, z_2 \geq y_1, y_2 \geq 1$$

Similarly for the case $y \geq x$

Case 2.

If $y \not\geq x$ & $x \not\geq y$

$$\text{i.e. } (y_1 - x_1)(y_2 - x_2) < 0$$

$$\begin{aligned} z_1 z_2 &= (\theta x_1 + (1-\theta)y_1)(\theta x_2 + (1-\theta)y_2) \\ &= (\theta^2 x_1 x_2 + (1-\theta)^2 y_1 y_2 + \theta(1-\theta)x_1 y_2 + \theta(1-\theta)x_2 y_1) \\ &= \theta^2 x_1 x_2 + y_1 y_2 + \theta^2 y_1 y_2 - 2\theta y_1 y_2 + \theta(1-\theta) [x_1 y_2 + x_2 y_1] \\ &= \theta x_1 x_2 + (1-\theta)y_1 y_2 - \theta(1-\theta)(y_1 - x_1)(y_2 - x_2) \\ &\geq 1. \end{aligned}$$

Hence $z \in S$.

Show that $\{x \in (x_1, x_2, \dots, x_n) \in \mathbb{R}_+^n \mid \prod_{i=1}^n x_i \geq 1\}$ is convex consider a convex combination

x of 2 points,

$$x = (x_1, x_2, \dots, x_n) \& y = (y_1, y_2, \dots, y_n) \text{ belonging to } S.$$

$$\prod_{i=1}^n x_i \geq 1 \quad \& \quad \prod_{i=1}^n y_i = 1 \quad \left[\text{since } x \& y \text{ belong to } S \right]$$

Case 1 $x \geq y$.

$$z = \theta x + (1-\theta)y \geq y.$$

$$\& \quad z_1 z_2 \cdots z_n \geq y_1 y_2 \cdots y_n \geq 1.$$

Similarly for case $y \geq x$.

Case 2 If $y \not\geq x$ & $x \geq y$
i.e.

$$(y_1 - z_1)(y_2 - z_2)(y_3 - z_3) \cdots (y_n - z_n) < 0.$$

Inequality 1: If $\alpha, \beta \geq 0$ & $0 \leq \theta \leq 1$
then $\alpha^\theta \beta^{1-\theta} \leq \theta \alpha + (1-\theta)\beta$.

Using the above inequality,

$$\begin{aligned} z_1 z_2 \cdots z_n &= \prod_{i=1}^n (\theta x_i + (1-\theta)y_i) \geq \prod_{i=1}^n x_i^\theta y_i^{(1-\theta)} \\ &\geq \left(\prod_{i=1}^n x_i \right)^\theta \left(\prod_{i=1}^n y_i \right)^{1-\theta} \\ &\geq 1 \end{aligned}$$

Hence $x \in S$.

Q. 4(c) Show that S is convex iff its intersection with any line is convex.

Theorem A: Intersection of 2 convex sets is convex.

⇒

Using Theorem A, if S is convex set then the intersection of S with a line is also convex set.

⇐ Suppose the intersection of S with any line is convex, take any 2 points x_1 & $x_2 \in S$.

The intersection of S with the line through x_1 & x_2 is convex.

∴ convex combination of x_1 & x_2 belong to the intersection, hence they also belong to S .

Show that S is affine iff its intersection with line is affine.

The above statement can be proved similarly as in the case of convex sets, instead of convex sets, we use affine sets.

Q.4(d) Let $\text{conv}(S)$ be the convex hull of S and let C be the intersection of all convex sets containing S , i.e.

$$C = \bigcap \{C \mid C \text{ is convex, } C \supseteq S\}$$

To show: $\text{conv}(S) = C$.

For this, we need to show that

$$\text{conv}(S) \subseteq C \text{ and } C \subseteq \text{conv}(S)$$

1) $\text{conv}(S) \subseteq C$

Let x be a convex combination of some points $x_1, x_2, \dots, x_n \in S$, or $x \in \text{conv}(S)$. — (A)

Let C be any convex set containing S ($C \supseteq S$).
 $\therefore x_1, x_2, \dots, x_n \in C$. — (B)

From A & B $\Rightarrow x \in C$ — (C)

From (C), for any convex set C , that contains S , $x \in C$, i.e. x also belongs to intersection of all such convex sets C containing S .

$$\therefore x \in C.$$

$$\Rightarrow \text{conv}(S) \subseteq C$$

2.) $C \subseteq \text{conv}(S)$

Since $\text{conv}(S)$ is a convex set containing

(d) continued.

S, we must have $\text{convsh}(S) = c$ for some c during construction of c .

Hence proved.

From ① & ②. $\Rightarrow \text{convsh}(c) = c$.

The above proof can also be used for affine & ~~conv~~ conic hulls as well, instead of convex combinations, we use affine & conical combinations for them.

Q.4(e) $S = \{ x \mid \|x - a\|_2 \leq \theta \|x - b\|_2 \}$
 $a \neq b$ are fixed points
 $0 \leq \theta \leq 1$.

We assume that $a \neq b$.

$$S = \{ x \mid \|x - a\|_2^2 \leq \theta^2 \|x - b\|_2^2 \}$$

$$= \{ x \mid (1 - \theta^2) x^T x - 2(a - \theta^2 b)^T x + a^T a - \theta^2 b^T b \leq 0 \}.$$

case 1. When $\theta = 1$.

2) it is a half space.

case 2 $\theta < 1$.

2) it is a ball

$$\{ x \mid (x - z_0)^T (x - z_0) \leq r^2 \}$$

case 1 & case 2 $\Rightarrow S$ is convex.