

# CS446: Machine Learning, Fall 2018, Homework 0

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## Problem (1)

(a)

Note that both  $H_1$  and  $H_{-1}$  are parallel hyperplanes, since their normal vectors are equal. It follows that to find the distance between both planes, given a point  $x_1$  lying on  $H_1$ , the closest point on  $H_{-1}$  to  $x_1$  is the point  $x_2$  obtained from intersecting the line  $\{x_1 + wt | t \in \mathbb{R}\}$  with  $H_{-1}$ . That is  $x_2 = x_1 + wt$ . We seek to find  $\|wt\|$ . Note that  $w^T x_1 = 1$  and  $w^T x_2 = -1$ . Hence:

$$\begin{aligned} x_2 - x_1 &= wt \\ \Rightarrow w^T(x_2 - x_1) &= (w^T w)t \\ \Rightarrow -2 &= \|w\|^2 t \\ \Rightarrow t &= \frac{-2}{\|w\|^2} \\ \Rightarrow \|wt\| &= \left\| \left[ w \left( \frac{-2}{\|w\|^2} \right) \right] \right\| \\ &= \frac{2}{\|w\|} \end{aligned}$$

(b)

We prove this by contradiction. Suppose that there is a better maximum margin classifier  $w' \neq w$  for the set  $(X^*, Y^*)$ . We will show that  $w'$  is also the maximum margin classifier for  $(X, Y)$  then, which is a contradiction, since we assumed that  $w$  was the maximum margin classifier and the maximum margin classifier is unique<sup>1</sup>

By assumption, since  $w'$  is a better classifier for  $(X^*, Y^*)$ ,

$$y^i(w')^T x^i \geq 1 \quad \text{for all } i \in \mathcal{N} \text{ and} \quad (\gamma)$$

$$\frac{2}{\|w'\|} \geq \frac{2}{\|w\|}$$

Thus, to prove that  $w'$  is the maximum margin classifier for  $(X, Y)$ , we need to show that

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<sup>1</sup>Solving for the maximum margin classifier in the separable case is a strictly convex problem and, hence, the minimizer to the problem is unique.

$$y^j(w')^T x^j \geq 1 \quad \text{For all } j \notin \mathcal{N}$$

Let  $H_1 = \{(x, 1) \in (\mathbb{R}^n, \mathbb{R}^n) | (1)w^T x = 1\}$ . Without loss of generality, consider any  $(x^j, y^j)$  for  $j \notin \mathcal{N}$  such that  $y^j = 1$ . There exists some  $(z, 1) \in H_1$  such that  $z + \alpha w = x^j$ , where  $\alpha > 0$ . Thus

$$\begin{aligned} y^j(w')^T x^j &= y^j \alpha (w')^T (z + w) \\ &= y^j (w')^T z + y^j \alpha (w')^T w \\ &\geq 1 + y^j \alpha (w')^T w \\ &= 1 + \alpha (w')^T w \end{aligned}$$

It suffices to show that  $(w')^T w \geq 0$ , to prove that  $(x^j, y^j)$  is correctly classified using  $w'$ .

Observe that for any  $\beta > 0$ , we must have that  $\beta w$  is classified using the maximum margin classifier under  $w$ , which we label  $\mathcal{A}_w$ , as having label 1. For if  $q$  is the label of  $\beta w$ , then

$$\mathcal{A}_w(\beta w) = q(w^T(\beta w)) > 0 \implies q = 1$$

Thus, in particular, there exists some  $\beta' > 0$  such that  $\mathcal{A}_w(\beta' w) = 1$ , meaning that  $\beta' w$  lies on  $H_1$  and we must have, by construction,  $(w')^T(\beta' w) > 0 \implies (w')^T w \geq 0$ .

Thus  $w'$  correctly classifies even  $(x^j, y^j)$ . Since  $j \notin \mathcal{N}$  was arbitrary,  $\mathcal{A}'_w$  correctly classifies all  $j \notin \mathcal{N}$ .  $\mathcal{A}'_w$  already correctly classified those  $(x^i, y^i) \in \mathcal{N}$  and  $\frac{2}{\|w'\|} \geq \frac{2}{\|w\|}$ , so we conclude that  $w'$  is a better classifier than  $w$  for  $(X, Y)$ , which is a contradiction.