

# Introduction to Machine Learning - hw 3 - short

Omer Simhi, 316572593

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1. For the (homogeneous) linearly separable case:

(a) When  $\lambda \rightarrow \infty$  to which solution will the soft SVM converge?

Solution - Notice that:

$$\begin{aligned} \lim_{\lambda \rightarrow \infty} \left( \operatorname{argmin}_{w \in \mathbb{R}^d} \left( \frac{1}{m} \cdot \sum_{i=1}^m \max \{0, 1 - y_i w^T x_i\} + \lambda \|w\|_2^2 \right) \right) &\approx \\ &\approx \lim_{\lambda \rightarrow \infty} \left( \operatorname{argmin}_{w \in \mathbb{R}^d} \left( \lambda \|w\|_2^2 \right) \right) \end{aligned}$$

since the effect of  $\frac{1}{m} \cdot \sum_{i=1}^m \max \{0, 1 - y_i w^T x_i\}$  when  $\lambda \rightarrow \infty$  is negligible compare to  $\lambda \|w\|_2^2$ . Notice that  $\lim_{\lambda \rightarrow \infty} \left( \operatorname{argmin}_{w \in \mathbb{R}^d} \left( \lambda \|w\|_2^2 \right) \right) < \infty$  iff  $\|w\|_2^2 = 0$  otherwise  $\lim_{\lambda \rightarrow \infty} \left( \operatorname{argmin}_{w \in \mathbb{R}^d} \left( \lambda \|w\|_2^2 \right) \right) = \infty$ . So we get  $\|w\|_2 = 0$  and so  $w = 0$  is the only way to minimize the expression.

(b) When  $\lambda \rightarrow 0$ , the soft SVM converges to the hard SVM's solution. Explain briefly and intuitively how it can be seen from the formulations above.

Solution - Recall that  $\lambda$  is the "tradeoff factor" between increasing the margin size and ensuring that each of  $x_i$  are in correct size of the margin. Now, as  $\lambda \rightarrow 0$  we get that the expression  $\lambda \|w\|_2^2$  is negligible and thus the problem became:  $\operatorname{argmin}_{w \in \mathbb{R}^d} \left( \frac{1}{m} \cdot \sum_{i=1}^m \max \{0, 1 - y_i w^T x_i\} \right)$ . Notice that this means that we can't have violations of margin constraints, and so the second term,  $1 - y_i w^T x_i$  is negligible so we returns to the hard SVM solution.

2. Let  $K_1(u, v) = \langle \phi_1(u), \phi_1(v) \rangle$ ,  $K_2(u, v) = \langle \phi_2(u), \phi_2(v) \rangle$  where  $\phi_1 : \mathcal{X} \rightarrow \mathbb{R}^{n_1}$ ,  $\phi_2 : \mathcal{X} \rightarrow \mathbb{R}^{n_2}$  s.t  $n_1, n_2 \in \mathbb{N}$ . Let's denote:

$$\begin{aligned}\phi_1(u) &= (u_1 \quad . \quad . \quad . \quad u_{n_1})^T, \phi_1(v) = (v_1 \quad . \quad . \quad . \quad v_{n_1})^T \\ \phi_2(u) &= (u'_1 \quad . \quad . \quad . \quad u'_{n_2})^T, \phi_2(v) = (v'_1 \quad . \quad . \quad . \quad v'_{n_2})^T\end{aligned}$$

We get:

$$K_3(u, v) := K_1(u, v) + K_2(u, v) = \langle \phi_1(u), \phi_1(v) \rangle + \langle \phi_2(u), \phi_2(v) \rangle$$

$$\begin{aligned}&= \sum_{i=1}^{n_1} u_i v_i + \sum_{j=1}^{n_2} u'_j v'_j = (u_1 \quad . \quad . \quad . \quad u_{n_1} \quad u'_1 \dots u'_{n_2}) \begin{pmatrix} v_1 \\ . \\ . \\ v_{n_1} \\ v'_1 \\ . \\ . \\ . \\ v'_{n_2} \end{pmatrix} = \\&= \langle (u_1 \quad . \quad . \quad . \quad u_{n_1} \quad u'_1 \dots u'_{n_2}), (v_1 \quad . \quad . \quad . \quad v_{n_1} \quad v'_1 \dots v'_{n_2}) \rangle = \langle \phi_1(u) \phi_2(u), \phi_1(v) \phi_2(v) \rangle\end{aligned}$$

where  $\phi_1(u) \phi_2(u)$  is the concatenation of  $\phi_1(u)$  to  $\phi_2(u)$ . So, if we define  $\phi_3 : \mathcal{X} \rightarrow \mathbb{R}^{n_3}$  with  $n_3 := n_1 + n_2$  and:

$$\phi_3(x) = (\phi_1(x) \phi_2(x))^T$$

we get finally  $K_3(u, v) = \langle \phi_3(u), \phi_3(v) \rangle$  as required.

3. Define the hypothesis class of axis aligned rectangles (or cuboids) in  $\mathbb{R}^d$  -

$$\mathcal{H} = \mathbb{R}^d, \mathcal{H}_{rect}^d = \left\{ h_\theta \mid \forall i \in [d] : \theta_i^{(1)} < \theta_i^{(2)} \right\}$$

where  $\theta^{(1)}, \theta^{(2)} \in \mathbb{R}^d$ ,  $\theta = (\theta^{(1)}, \theta^{(2)})$  and  $h_\theta(x) = \begin{cases} 1 & \wedge_{i \in [d]} \left( \theta_i^{(1)} \leq x_i \leq \theta_i^{(2)} \right) \\ -1 & \text{otherwise} \end{cases}$

(a) Explain in your own simple words (1-3 sentences), what do we need to show in order to prove that  $VCdim(\mathcal{H}_{rect}^d) = k$  for some  $k \in \mathbb{N}$ .

Solution - We will show two things by definition:

- There exist a sample set  $S$  with size  $k$  s.t  $\exists h_\theta \in \mathcal{H}_{rect}^d$  that shatter  $S$  for any given labels set for the set  $S$ .
- For any sample set  $S$  with size  $k + 1$  there is no  $h_\theta \in \mathcal{H}_{rect}^d$  that shatter  $S$ .

(b) Prove that  $VCdim(\mathcal{H}_{rect}^d) \geq 2d$ .

Solution - Let us consider the following set  $S$ :

$$S = \bigcup_{i=1}^d \{e_i^+, e_i^-\}$$

$$e_i^+ := \left( 0, 0, \dots, \underbrace{1}_i, 0, \dots, 0 \right), e_i^- := \left( 0, 0, \dots, \underbrace{-1}_i, 0, \dots, 0 \right)$$

clearly  $|S| = 2d$ . Denote an arbitrary set of labels  $Y := \{y_1, y'_1, \dots, y_d, y'_d\}$  for the  $2d$  points of  $S$  where  $y_i$  is the label of  $e_i^+$  and  $y'_i$  is the label of  $e_i^-$ . Now, for  $i = 1, 2, \dots, d$  define  $\theta_i^{(1)}, \theta_i^{(2)}$  for each option of labels:

- i.  $y_i = 1, y'_i = 1$  - define  $\theta_i^{(1)} = -2, \theta_i^{(2)} = 2$
- ii.  $y_i = -1, y'_i = 1$  - define  $\theta_i^{(1)} = -0.5, \theta_i^{(2)} = 2$
- iii.  $y_i = 1, y'_i = -1$  - define  $\theta_i^{(1)} = -2, \theta_i^{(2)} = 0.5$
- iv.  $y_i = -1, y'_i = -1$  - define  $\theta_i^{(1)} = -0.5, \theta_i^{(2)} = 0.5$

Notice that  $h_\theta$  obtained this way is in  $\mathcal{H}_{rect}^d$  since its  $d$  - dimension rectangle. In addition, notice that the  $i$ th sample is in this rectangle iff the  $i$ th component of the sample is in  $(\theta_i^{(1)}, \theta_i^{(2)})$ . Now, 0 always in this range, and since all the components of sample  $i$  are 0 beside the  $i$ th component, then from the construction above, we get correct labeling for all samples and so we successfully shattered  $S$  with  $\mathcal{H}_{rect}^d$ .

4. Prove that  $VCdim(\mathcal{H}_{rect}^d) = 2d$ .

Solution - Using section (b) it's suffice to prove  $VCdim(\mathcal{H}_{rect}^d) < 2d + 1$ . Let  $S$  be any sample set with  $2d + 1$  points. Define the rectangle with  $\theta_i^{(1)} = \min_i$  and  $\theta_i^{(2)} = \max_i$  where  $\min_i$  is the minimum value of all  $i$ th components of the samples and  $\max_i$  the maximum value of all  $i$ th components of the samples. Now, notice that from the pigeonhole principle, since we have  $2d + 1$  points, at least one point is right inside this rectangle. If we lable this point by  $-1$  and all the rest with  $+1$  we clearly can't find a rectangle that separates this labeling correctly. Thus, the by defenition  $VCdim(\mathcal{H}_{rect}^d) < 2d + 1$  as required.