

# HW2

November 2, 2016

## A. Rademacher Complexity

1.

$$\begin{aligned}
 \mathcal{R}'(h) &= \frac{1}{m} \mathbf{E}_{\sigma, S} \left[ \sup_{h \in H} \left| \sum_{i=1}^m \sigma_i h(x_i) \right| \right] \\
 &\leq \frac{1}{m} \mathbf{E}_{\sigma, S} \left[ \sup_{h \in H} \sum_{i=1}^m |\sigma_i| |h(x_i)| \right] \\
 &\leq \frac{1}{m} \mathbf{E}_S [m \sup_{h \in H} |h(x)|] \\
 &\leq \frac{1}{m} \sqrt{m \mathbf{E}_S [\sup_{h \in H} (|h(x)|)^2]} \\
 &= \frac{1}{m} \sqrt{m \mathbf{E}_{x \sim D} [h^2(x)]} \\
 &= \sqrt{\frac{\mathbf{E}_{x \sim D} [h^2(x)]}{m}}
 \end{aligned}$$

2.

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$$\begin{aligned}
 \mathcal{R}_m(\alpha H) &= \mathbf{E}_{\sigma} \left[ \sup_{h \in H} \frac{1}{m} \sum_{i=1}^m \sigma_i \alpha h(x_i) \right] \\
 &= \mathbf{E}_{\sigma'} \left[ |\alpha| \sup_{h \in H} \frac{1}{m} \sum_{i=1}^m \sigma'_i h(x_i) \right] \\
 &= |\alpha| \mathcal{R}_m(H)
 \end{aligned}$$

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$$\begin{aligned}
 \mathcal{R}_m(H + H') &= \mathbf{E}_{\sigma} \left[ \sup_{h \in H, h' \in H'} \frac{1}{m} \sum_{i=1}^m \sigma_i (h(x_i) + h'(x_i)) \right] \\
 (\text{subadditivity}) &\leq \mathbf{E}_{\sigma} \left[ \sup_{h \in H} \frac{1}{m} \sum_{i=1}^m \sigma_i h(x_i) + \sup_{h' \in H'} \frac{1}{m} \sum_{i=1}^m \sigma_i h'(x_i) \right] \\
 &= \mathcal{R}_m(H) + \mathcal{R}_m(H')
 \end{aligned}$$

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$$\begin{aligned}
\mathcal{R}_m(\{max(h, h') : h \in H, h' \in H'\}) &= \mathbf{E}_\sigma \left[ \sup_{h \in H, h' \in H'} \frac{1}{m} \sum_{i=1}^m \sigma_i max((h(x_i), h'(x_i))) \right] \\
&= \mathbf{E}_\sigma \left[ \sup_{h \in H, h' \in H'} \frac{1}{m} \sum_{i=1}^m \sigma_i \frac{1}{2} [h(x_i) + h'(x_i) + |h(x_i) - h'(x_i)|] \right] \\
(\text{Lipschitz}) &\leq \frac{1}{2} \mathbf{E}_\sigma \left[ \sup_{h \in H, h' \in H'} \frac{1}{m} \sum_{i=1}^m \sigma_i [h(x_i) + h'(x_i) + |h(x_i) - h'(x_i)|] \right] \\
(\text{subadditivity}) &\leq \frac{1}{2} \mathbf{E}_\sigma \left[ \sup_{h \in H} \frac{1}{m} \sum_{i=1}^m \sigma_i h(x_i) + \sup_{h' \in H'} \frac{1}{m} \sum_{i=1}^m \sigma_i h'(x_i) \right. \\
&\quad \left. + \sup_{h \in H} \frac{1}{m} \sum_{i=1}^m \sigma_i h(x_i) + \sup_{h' \in H'} \frac{1}{m} \sum_{i=1}^m \sigma_i h'(x_i) \right] \\
&= \mathcal{R}_m(H) + \mathcal{R}_m(H')
\end{aligned}$$

## B. VC-dimension

1. Unlike *intervals on real line* in lecture, any three points can be shattered by the subset of real line. However, in four-point case,  $(+, -, +, -)$  cannot be shattered. So the VC-dimension is 3.
2. (a) Counter example:  $(+, -, -, -)$

$$\begin{cases} \omega x = (2k\pi, 2k\pi + \pi) \\ 2\omega x = (2k\pi + \pi, 2k\pi + 2\pi) \\ 3\omega x = (2k\pi + \pi, 2k\pi + 2\pi) \\ 4\omega x = (2k\pi + \pi, 2k\pi + 2\pi) \end{cases} \Rightarrow \begin{cases} \omega x = (2k\pi, 2k\pi + \pi) \\ \omega x = (k\pi + \frac{1}{2}\pi, k\pi + \pi) \\ \omega x = (\frac{2}{3}k\pi + \frac{1}{3}\pi, \frac{2}{3}k\pi + \frac{2}{3}\pi) \\ \omega x = (\frac{1}{2}k\pi + \frac{1}{4}\pi, \frac{1}{2}k\pi + \frac{1}{2}\pi) \end{cases} \quad (1)$$

Note, there is no intersection among these four regions no matter how  $k$  is chosen. So for any  $x \in \mathbb{R}$ ,  $x, 2x, 3x, 4x$  cannot be shattered by the family of sine functions.

- (b) Similarly,

$$\omega \in 2^m(2k\pi, 2k\pi + \pi)$$

for positive points, and

$$\omega \in 2^m(2k\pi + \pi, 2k\pi + 2\pi)$$

for negative ones.

For  $m = 0$ , for a particular point,  $\omega$  could only be in half of the space, while for  $m > 0$ , positive or negative,  $\omega$  covers all the space of the value of sine functions. That is to say,  $\forall \omega \in \mathbb{N}$ , there is a selection of  $\omega$  such that  $\{2^{-m}\}$  can be fully shattered.

## C. Support Vector Machine

1. The splitting, scaling, training and testing operations are written as script.
2. In my experient,  $C^* = 4$   
I know my script goes wrong because  $d$  value does not matter. I tested on cross validation and test data, and I also checked the number of SV, they were all the same, with value 15, 15, 1919.
3. If the penalty because  $\|\xi\|_\infty$ , the only difference is  $\nabla_{\xi_i} L$  in  $KKT$ , which becomes  $\alpha_i + \beta_i = C \mathbf{1}_{\xi_i = \max_j \xi_j}$ . The goal function of the dual problem does not change, only constraint  $0 \leq \alpha_i \leq C$  changes to  $0 \leq \|\alpha\|_\infty \leq C$ .

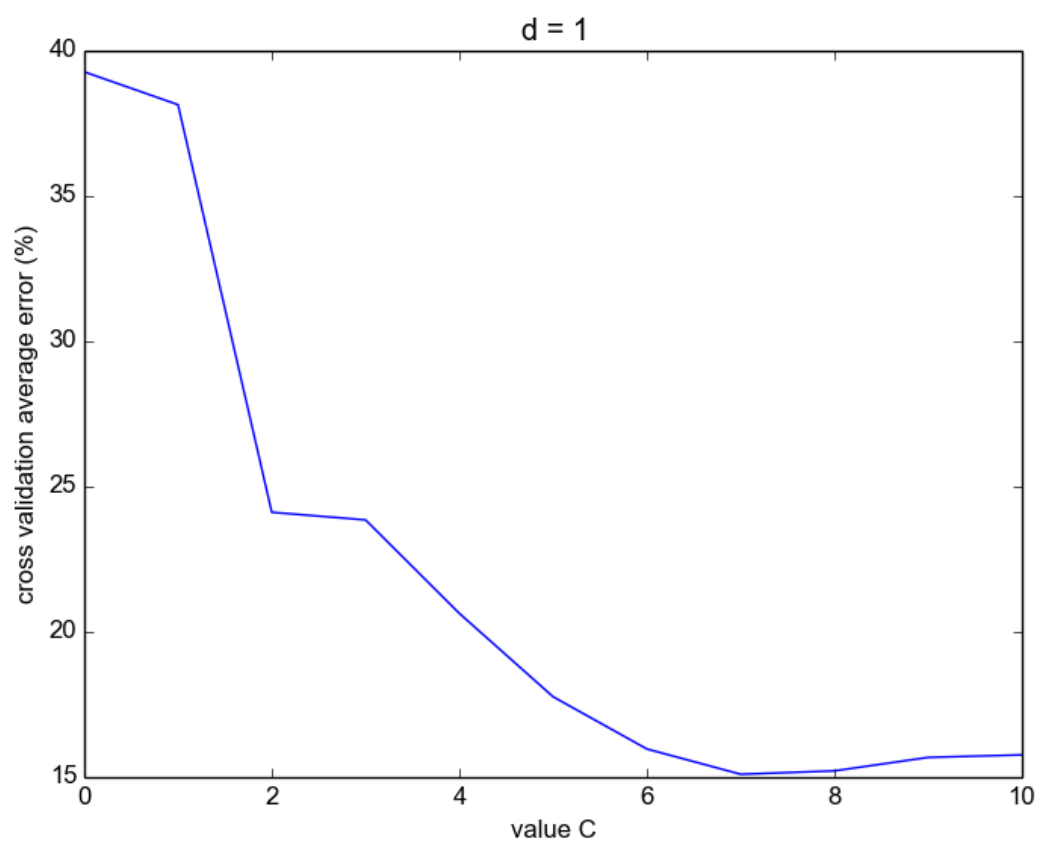


Figure 1: Average cross validation error versus C.