

Theory of Machine Learning: Homework 3

1. Let $\mathcal{H} = \{\mathbf{x} \rightarrow \langle \mathbf{w}, \mathbf{x} \rangle \text{ s.t. } \|\mathbf{w}\|_2 \leq 1\}$ be linear classifiers. Let $S_x = (\mathbf{x}_1, \dots, \mathbf{x}_m) \subset \mathbb{R}^n$ be a training set with Frobenius norm $\|S_x\|_F^2 = \sum_{i=1}^m \|\mathbf{x}_i\|_2^2$. Define $\mathcal{H} \circ S_x = \{(a_1, \dots, a_m) \text{ s.t. } h \in \mathcal{H}, a_i = h(\mathbf{x}_i)\}$.

- (a) We want to show that $\hat{\mathcal{R}}_S(\mathcal{H} \circ S_x) \leq \frac{1}{m} \mathbb{E}_\sigma \left[\left\| \sum_{i=1}^m \sigma_i \mathbf{x}_i \right\|_2 \right]$.

Proof. We first want to double check that an inequality we use frequently is correct. Suppose

$$\forall t, f(t) \leq g(t) \implies \forall t, f(t) \leq g(t) \leq \sup_t g(t) \implies \sup_t f(t) \leq \sup_t g(t)$$

The empirical Rademacher complexity is given by

$$\hat{\mathcal{R}}_S(F) = \mathbb{E}_\sigma \left[\sup_{f \in F} \frac{1}{m} \sum_{i=1}^m \sigma_i f(z_i) \right].$$

With $F = \mathcal{H} \circ S_x$, we can rewrite this as:

$$\begin{aligned} \hat{\mathcal{R}}_S(\mathcal{H} \circ S_x) &= \mathbb{E}_\sigma \left[\sup_{\|\mathbf{w}\| \leq 1} \frac{1}{m} \sum_{i=1}^m \sigma_i \langle \mathbf{w}, \mathbf{x}_i \rangle \right] \\ &= \frac{1}{m} \mathbb{E}_\sigma \left[\sup_{\|\mathbf{w}\| \leq 1} \sum_{i=1}^m \sigma_i \langle \mathbf{w}, \mathbf{x}_i \rangle \right] \\ &= \frac{1}{m} \mathbb{E}_\sigma \left[\sup_{\|\mathbf{w}\| \leq 1} \left\langle \mathbf{w}, \sum_{i=1}^m \sigma_i \mathbf{x}_i \right\rangle \right] \quad (\text{bilinearity of the inner product}) \\ &\leq \frac{1}{m} \mathbb{E}_\sigma \left[\sup_{\|\mathbf{w}\| \leq 1} \left| \left\langle \mathbf{w}, \sum_{i=1}^m \sigma_i \mathbf{x}_i \right\rangle \right| \right] \\ &\leq \frac{1}{m} \mathbb{E}_\sigma \left[\sup_{\|\mathbf{w}\| \leq 1} \|\mathbf{w}\|_2 \left\| \sum_{i=1}^m \sigma_i \mathbf{x}_i \right\|_2 \right] \quad (\text{Holder's inequality}) \\ \implies \hat{\mathcal{R}}_S(\mathcal{H} \circ S_x) &\leq \frac{1}{m} \mathbb{E}_\sigma \left[\left\| \sum_{i=1}^m \sigma_i \mathbf{x}_i \right\|_2 \right] \end{aligned}$$

QED

- (b) We want to show that $\hat{\mathcal{R}}_S(\mathcal{H} \circ S_x) \leq \frac{1}{m} \|S_x\|_F$.

Proof. Let $g(t) = -\sqrt{t}$.

$$g'(t) = -\frac{1}{2}t^{-1/2} \implies g''(t) = \frac{1}{4}t^{-3/2}$$

For $t \in (0, \infty)$ it is true that $g''(t) > 0$ (g is convex). For an r.v. θ Jensen's inequality therefore says

$$g(\mathbb{E}[\theta]) \leq \mathbb{E}[g(\theta)] \implies -\sqrt{\mathbb{E}[\theta]} \leq \mathbb{E}[-\sqrt{\theta}] \implies \mathbb{E}[\sqrt{\theta}] \leq \sqrt{\mathbb{E}[\theta]}$$

So:

$$\begin{aligned} \hat{\mathcal{R}}_S(\mathcal{H} \circ S_x) &\leq \frac{1}{m} \mathbb{E}_\sigma \left[\left\| \sum_{i=1}^m \sigma_i \mathbf{x}_i \right\|_2 \right] \quad (\text{result of (a)}) \\ &= \frac{1}{m} \mathbb{E}_\sigma \left[\sqrt{\left\| \sum_{i=1}^m \sigma_i \mathbf{x}_i \right\|_2^2} \right] \\ &\leq \frac{1}{m} \sqrt{\mathbb{E}_\sigma \left[\left\| \sum_{i=1}^m \sigma_i \mathbf{x}_i \right\|_2^2 \right]} \quad (\text{Jensen's inequality}) \\ &= \frac{1}{m} \sqrt{\mathbb{E}_\sigma \left[\left\langle \sum_{i=1}^m \sigma_i \mathbf{x}_i, \sum_{i=1}^m \sigma_i \mathbf{x}_i \right\rangle \right]} \end{aligned}$$

$$\begin{aligned}
&= \frac{1}{m} \sqrt{\mathbb{E}_\sigma \left[\sum_{i=1}^m \sum_{j=1}^m \sigma_i \sigma_j \langle \mathbf{x}_i, \mathbf{x}_j \rangle \right]} \quad (\text{bilinearity of the inner product}) \\
&= \frac{1}{m} \sqrt{\sum_{i=1}^m \sum_{j=1}^m \mathbb{E}_\sigma [\sigma_i \sigma_j] \langle \mathbf{x}_i, \mathbf{x}_j \rangle} \quad (\text{linearity of the expectation})
\end{aligned}$$

When $i = j$, $\sigma_i \sigma_j = \sigma_i^2 \implies \mathbb{E}_\sigma [\sigma_i \sigma_j] = 1$. When $i \neq j$, $\mathbb{E}_\sigma [\sigma_i \sigma_j] = \mathbb{E}[\sigma_i] \mathbb{E}[\sigma_j] = 0$ by independence. So:

$$\begin{aligned}
\hat{\mathcal{R}}_S(\mathcal{H} \circ S_x) &\leq \frac{1}{m} \sqrt{\sum_{i=1}^m \sum_{j=1}^m \mathbb{E}_\sigma [\sigma_i \sigma_j] \langle \mathbf{x}_i, \mathbf{x}_j \rangle} \\
&= \frac{1}{m} \sqrt{\sum_{i=1}^m \langle \mathbf{x}_i, \mathbf{x}_i \rangle} \\
&= \frac{1}{m} \sqrt{\sum_{i=1}^m \|\mathbf{x}_i\|_2^2} \\
&\implies \hat{\mathcal{R}}_S(\mathcal{H} \circ S_x) \leq \frac{1}{m} \|S_x\|_F
\end{aligned}$$

QED

(c) Now suppose $D \sim \mathcal{N}(0, I_{n \times n})$. We want to bound the Rademacher complexity $\mathcal{R}_m(\mathcal{H})$.

Proof.

$$\begin{aligned}
\hat{\mathcal{R}}_S(\mathcal{H} \circ S_x) &\leq \frac{1}{m} \|S_x\|_F \\
\mathbb{E}_{S_x \sim D^m} [\hat{\mathcal{R}}_S(\mathcal{H} \circ S_x)] &\leq \mathbb{E}_{S_x \sim D^m} \left[\frac{1}{m} \|S_x\|_F \right] \quad (\text{monotonicity of the expectation}) \\
\text{So, } \mathcal{R}_m(\mathcal{H}) &\leq \frac{1}{m} \mathbb{E}_{S_x \sim D^m} [\|S_x\|_F] \\
&= \frac{1}{m} \mathbb{E}_{S_x \sim D^m} \left[\sqrt{\sum_{i=1}^m \|\mathbf{x}_i\|_2^2} \right] \\
&\leq \frac{1}{m} \sqrt{\mathbb{E}_{S_x \sim D^m} \left[\sum_{i=1}^m \|\mathbf{x}_i\|_2^2 \right]} \quad (\text{Jensen's inequality}) \\
&= \frac{1}{m} \sqrt{\sum_{i=1}^m \mathbb{E}_{S_x \sim D^m} [\|\mathbf{x}_i\|_2^2]} \quad (\text{linearity of the expectation}) \\
&= \frac{1}{m} \sqrt{\sum_{i=1}^m \mathbb{E}_{S_x \sim D^m} \left[\sum_{j=1}^n (\mathbf{x}_i)_j^2 \right]} \\
&= \frac{1}{m} \sqrt{\sum_{i=1}^m \sum_{j=1}^n \mathbb{E}_{S_x \sim D^m} [(\mathbf{x}_i)_j^2]} \quad (\text{linearity of the expectation})
\end{aligned}$$

Based on the given D , we know $(\mathbf{x}_i)_j \sim \mathcal{N}(0, 1)$. We know that

$$\begin{aligned}
\text{Var}[(\mathbf{x}_i)_j] &\leq \mathbb{E}[(\mathbf{x}_i)_j^2] - \mathbb{E}[(\mathbf{x}_i)_j]^2 \\
&= 1 - 0^2 \\
&\implies \mathbb{E}[(\mathbf{x}_i)_j^2] = 1
\end{aligned}$$

So:

$$\mathcal{R}_m(\mathcal{H}) \leq \frac{1}{m} \sqrt{\sum_{i=1}^m \sum_{j=1}^n \mathbb{E}_{S_x \sim D^m} [(\mathbf{x}_i)_j^2]}$$

$$\begin{aligned}
&= \frac{1}{m} \sqrt{\sum_{i=1}^m \sum_{j=1}^n 1} \\
&= \frac{1}{m} \sqrt{mn} \\
\Rightarrow \mathcal{R}_m(\mathcal{H}) &\leq \sqrt{\frac{n}{m}}
\end{aligned}$$

QED