CMSC 35900 (Spring 2008) Learning Theory

Lecture: 10

Massart's Finite Class Lemma and Growth Function

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1 Growth function

Consider the case $\mathcal{Y} = \{\pm 1\}$ (classification). Let ϕ be the 0-1 loss function and \mathcal{F} be a class of ± 1 -valued functions. We can relate the Rademacher average of $\phi_{\mathcal{F}}$ to that of \mathcal{F} as follows.

Lemma 1.1. Suppose $\mathcal{F} \subseteq \{\pm 1\}^{\mathcal{X}}$ and let $\phi(y', y) = \mathbf{1} [y' \neq y]$ be the 0-1 loss function. Then we have,

$$\mathfrak{R}_m(\phi_{\mathcal{F}}) = \frac{1}{2}\mathfrak{R}_m(\mathcal{F}) \; .$$

Proof. Note that we can write $\phi(y', y)$ as (1 - yy')/2. Then we have,

$$\begin{aligned} \mathfrak{R}_{m}(\phi_{\mathcal{F}}) &= \mathbb{E} \left[\sup_{f \in \mathcal{F}} \frac{1}{m} \sum_{i=1}^{m} \epsilon_{i} \frac{1 - Y_{i}f(X_{i})}{2} \middle| X_{1}^{m}, Y_{1}^{m} \right] \\ &= \mathbb{E} \left[\sup_{f \in \mathcal{F}} \frac{1}{m} \sum_{i=1}^{m} \epsilon_{i} \frac{Y_{i}f(X_{i})}{2} \middle| X_{1}^{m}, Y_{1}^{m} \right] \end{aligned} \tag{1}$$

$$&= \frac{1}{2} \mathbb{E} \left[\sup_{f \in \mathcal{F}} \frac{1}{m} \sum_{i=1}^{m} (-\epsilon_{i}Y_{i})f(X_{i}) \middle| X_{1}^{m}, Y_{1}^{m} \right] \\ &= \frac{1}{2} \mathbb{E} \left[\sup_{f \in \mathcal{F}} \frac{1}{m} \sum_{i=1}^{m} \epsilon_{i}f(X_{i}) \middle| X_{1}^{m}, Y_{1}^{m} \right] \\ &= \frac{1}{2} \mathfrak{R}_{m}(\mathcal{F}) . \end{aligned}$$

Equation (1) follows because $\mathbb{E}[\epsilon_i | X_1^m, Y_1^m] = 0$. Equation (2) follows because $-\epsilon_i Y_i$'s jointly have the same distribution as ϵ_i 's.

Note that the Rademacher average of the class $\mathcal F$ can also be written as

$$\mathfrak{R}_m(\mathcal{F}) = \mathbb{E}\left[\sup_{a \in \mathcal{F}_{|X_1^m}} \frac{1}{m} \sum_{i=1}^m \epsilon_i a_i\right] ,$$

where $\mathcal{F}_{|X_1^m}$ is the function class \mathcal{F} restricted to the set X_1, \ldots, X_m . That is,

$$\mathcal{F}_{|X_1^m} := \{ ((f(X_1), \dots, f(X_m)) | f \in \mathcal{F} \}$$

Note that $\mathcal{F}_{|X_1^m}$ is finite and

$$|\mathcal{F}_{|X_1^m}| \le \min\{|\mathcal{F}|, 2^m\}$$

Thus we can define the growth function as

$$\Pi_{\mathcal{F}}(m) := \max_{x_1^m \in \mathcal{X}^m} |\mathcal{F}_{|x_1^m|}|.$$

The following lemma due to Massart allows us to bound the Rademacher average in terms of the growth function.

Finite Class Lemma (Massart). Let \mathcal{A} be some finite subset of \mathbb{R}^m and $\epsilon_1, \ldots, \epsilon_m$ be independent Rademacher random variables. Let $r = \sup_{a \in \mathcal{A}} ||a||$. Then, we have,

$$\mathbb{E}\left[\sup_{a\in\mathcal{A}}\frac{1}{m}\sum_{i=1}^{m}\epsilon_{i}a_{i}\right] \leq \frac{r\sqrt{2\ln|\mathcal{A}|}}{m}.$$

Proof. Let

$$\mu = \mathbb{E}\left[\sup_{a \in \mathcal{A}} \sum_{i=1}^{m} \epsilon_i a_i\right] \,.$$

We have, for any $\lambda > 0$,

$$\begin{split} e^{\lambda\mu} &\leq \mathbb{E}\left[\exp\left(\lambda \sup_{a \in \mathcal{A}} \sum_{i=1}^{m} \epsilon_{i} a_{i}\right)\right] & \text{Jensen's inequality} \\ &= \mathbb{E}\left[\sup_{a \in \mathcal{A}} \exp\left(\lambda \sum_{i=1}^{m} \epsilon_{i} a_{i}\right)\right] \\ &\leq \mathbb{E}\left[\sum_{a \in \mathcal{A}} \exp\left(\lambda \sum_{i=1}^{m} \epsilon_{i} a_{i}\right)\right] \\ &= \sum_{a \in \mathcal{A}} \mathbb{E}\left[\exp\left(\lambda \sum_{i=1}^{m} \epsilon_{i} a_{i}\right)\right] \\ &= \sum_{a \in \mathcal{A}} \prod_{i=1}^{m} \mathbb{E}\left[\exp\left(\lambda \epsilon_{i} a_{i}\right)\right] \\ &= \sum_{a \in \mathcal{A}} \prod_{i=1}^{m} e^{\lambda^{2} a_{i}^{2}/2} & \because \frac{e^{x} + e^{-x}}{2} \leq e^{x^{2}/2} \\ &= \sum_{a \in \mathcal{A}} e^{\lambda^{2} ||a||^{2}/2} \\ &\leq |\mathcal{A}|e^{\lambda^{2} r^{2}/2} \end{split}$$

Taking logs and dividing by λ , we get that, for any $\lambda > 0$,

$$\mu \leq \frac{\ln |\mathcal{A}|}{\lambda} + \frac{\lambda r^2}{2} \; .$$

Setting $\lambda = \sqrt{2 \ln |\mathcal{A}|/r^2}$ gives,

$$\mu \le r\sqrt{2\ln|\mathcal{A}|} \;,$$

which proves the lemma.