

Lecture 22: November 16, 2016

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Consider the problem of constrained least squares (possibly nonparametric). Here, we wish to bound $\|\hat{f} - f^*\|_n^2$ with high probability. Typically, the driving term for such a bound is the critical inequality

$$\frac{G_n(\delta, \mathcal{F})}{\delta} \leq \frac{\delta}{2\sigma}$$

It is often sharp for $\|\hat{f} - f^*\|_n^2$.

22.1 Example 1

For example, consider $\mathcal{F} = \{f_\theta, \theta \in B_q(R_q)\}$ where $f_\theta = \langle x, \theta \rangle$ with $x, \theta \in \mathbb{R}^d$ and

$$B_q(R_q) = \left\{ \theta \in \mathbb{R}^d : \sum_{i=1}^d |\theta_i|^q \leq R_q \right\}$$

with $q \in (0, 1)$. Here, $\theta \in B_q(R_q)$ implies that the coordinates of θ decay to 0 quickly (largest ones much greater than the others).

Consider

$$\hat{f} \in \operatorname{argmin}_{f \in \mathcal{F}} \frac{1}{2n} \sum_{i=1}^n (y_i - f(x_i))^2 \text{ for } x_1, \dots, x_n \text{ fixed.}$$

Then

$$\begin{aligned} \|\hat{f} - f^*\|_n^2 &= \frac{\|x(\hat{\theta} - \theta^*)\|^2}{n} \\ &\leq R_q \left(\frac{\sigma^2 \log(d)}{n} \right)^{1-q/2} \end{aligned}$$

where X is $n \times d$ with x_i as its i th row. This rate is minimax optimal. Here, the function class \mathcal{F} is not convex and is not star-shaped. We instead work with the class $d\mathcal{F} = \mathcal{F} - \mathcal{F} = \{f - g, f, g \in \mathcal{F}\}$ which is contained in $\mathcal{F}(2R_q) = \{f_\theta, \sum |\theta_i|^q \leq 2R_q\}$ and use the fact that

$$\log(N(\mu, \mathcal{F}, \|\cdot\|_{\text{euclid}})) \leq C_q R_q^{2/q} \left(\frac{1}{\mu} \right)^{2q/(2-q)} \log(d)$$

The same bound applies to the log covering number of $B_n(\delta, \mathcal{F}(2R_q))$ in $\|\cdot\|_n$ with $f \in \mathcal{F}(2R_q) : \|f\|_n \leq \delta$. So we need to evaluate

$$\frac{1}{\sqrt{n}} \int_0^\delta \sqrt{\log N(\mu, B_n(\delta, \mathcal{F}(2R_q)))} d\mu \leq R_q^{1/(2-q)} \sqrt{\frac{\log(d)}{n}} \delta^{1-q/(2-q)}$$

This is an upper bound on $G_n(\delta, \mathcal{F})$ (the local Gaussian complexity). Simply set it equal to δ^2 and solve for it. Sometimes upper bound the local entropy with that of the entire space.

22.2 Example 2

Consider nonparametric regression.

$$\mathcal{F} = \{f : [0, 1] \rightarrow \mathbb{R}, |f(x) - f(y)| \leq L|x - y| \text{ for all } x, y \in [0, 1]\}$$

and

$$y_i = f^*(x_i) + \delta w_i \text{ with } w_1, \dots, w_n \sim N(0, 1).$$

For this problem, consider the enlarged class $\mathcal{F}(2L) \supset \mathcal{F}(L) - \mathcal{F}(L)$. Use the fact that the metric entropy at scale μ is proportional to L/μ with respect to the L_∞ norm. So,

$$\begin{aligned} \frac{1}{\sqrt{n}} \int_0^\delta \sqrt{\log(N(\mu, B_n(\delta, \mathcal{F}(2L))))} d\mu \\ \propto \int_0^\delta \left(\frac{L}{\mu}\right)^{1/2} d\mu = C' \sqrt{\frac{L\delta}{n}} \end{aligned}$$

From the equation $\sqrt{L\delta_n/n} = \delta^2/\sigma$ which implies $\delta_n^2 = (L\sigma^2/n)^{2/3}$. Thus,

$$\|\hat{f} - f^*\|_n \propto \left(\frac{L\sigma^2}{n}\right)^{2/3} \text{ with high probability}$$

22.3 Oracle Inequality for Constrained Least Squares

So far we have assumed that $f^* \in \mathcal{F}$. If $f^* \notin \mathcal{F}$, then our benchmark becomes

$$\inf_{f \in \mathcal{F}} \|f - f^*\|_n^2$$

This the error that an oracle who knows f^* would make.

Theorem 22.1 *Assume that $d\mathcal{F} = \mathcal{F} - \mathcal{F}$ is star-shaped. Let δ_n be any positive solution to*

$$\frac{G_n(\delta, d\mathcal{F})}{\delta} \leq \frac{\delta}{2\sigma}.$$

Then there exists $c_0, c_1, c_2 > 0$ such that for all $t \geq \delta_n$,

$$\|\hat{f} - f^*\|_n^2 \leq \inf_{\gamma \in (0, 1)} \left\{ \frac{1 + \gamma}{1 - \gamma} \|f - f^*\|_n^2 + \frac{c_0 t \delta_n}{\gamma} \right\}$$

with probability greater than or equal to $1 - c_1 \exp(-c_2 n t \delta_n / \sigma^2)$.

Remarks:

1. We can rephrase it as

$$\|\hat{f} - f^*\|_n^2 \leq \frac{1 + \gamma}{1 - \gamma} \inf_{f \in \mathcal{F}} \|f - f^*\|_n^2 + \frac{c_0}{\gamma} + \delta_n$$

2. If $f^* \in \mathcal{F}$ then $\|\hat{f} - f^*\|_n^2 \leq \alpha \delta_n^2$.

3. Setting $t = \delta_n$ with $f^* \notin \mathcal{F}$, we get

$$\|\hat{f} - f^*\|_n^2 \leq \alpha \inf_{f \in \mathcal{F}} \|f - f^*\|_n^2 + \delta_n^2$$

The third point is like bias-variance tradeoff.

Proof: Let f be an arbitrary function in in \mathcal{F} . Then, from

$$\frac{1}{2n} \sum_{i=1}^n (y_i - \hat{f}(x_i))^2 \leq \frac{1}{2n} \sum_{i=1}^n (y_i - f(x_i))^2$$

we get

$$\frac{1}{2} \|\hat{\Delta}\|_n^2 \leq \frac{1}{2} \|f - f^*\|_n^2 + \sigma/n \left| \sum_{i=1}^n w_i \Delta_i \right|$$

where $\hat{\Delta} = \hat{f} - f^*$ and $\Delta = f - f^*$. We focus on the second term. Consider two cases:

1. $\|\Delta\|_n \leq \sqrt{t\delta_n}$. Then,

$$\begin{aligned} \|\Delta\|_n^2 &= \|\hat{f} - f + f - f^*\|_n^2 \\ &\leq (\|\Delta\|_n + \|f - f^*\|_n)^2 \\ &\leq \left(\sqrt{t\delta_n} + \|f - f^*\|_n \right)^2 \\ &= t\delta_n + \|f - f^*\|_n^2 + 2\sqrt{t\delta_n} \|f - f^*\|_n \\ &\text{Using the Young Fenchel inequality } xy \leq x^2/2\alpha + \alpha y^2/2, x, y \in \mathbb{R}, \alpha > 0 \\ &\leq t\delta_n + \|f - f^*\|_n^2 + t\delta_n/\alpha + \|f - f^*\|_n^2 \alpha \\ &\leq t\delta_n(1 + \alpha^{-1}) + \|f - f^*\|_n^2(1 + 2\alpha) \\ &\text{Set } \gamma = \alpha/(\alpha + 1) \\ &= \frac{t\delta_n}{\gamma} + \|f - f^*\|_n^2 \frac{1 + \gamma}{1 - \gamma} \end{aligned}$$

2. Otherwise, we can assume $\|\Delta\|_2 > \sqrt{t\delta_n}$. Here, $\Delta \in \mathcal{F}$, so applying Lemma 13.2 with $u = \sqrt{t\delta_n}$ yields

$$\mathbb{P}\left(2 \left| \frac{\sigma}{n} \sum_{i=1}^n w_i \Delta(x_i) \right| \geq (1 + 4\beta) \|f - f^*\|_n^2 + \frac{4}{\beta} t\delta_n \right)$$

due to the Young-Fenchel inequality with any $\beta > 0$. Setting $\beta = \gamma/(2(1-\gamma))$ followed by some algebra completes the proof. ■