Math 547: Mathematical Foundations of Statistical Learning Theory Fall 2017

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17.1 Symmetrization Inequality

Let $\mathcal{F} = \{f : S \to \mathbb{R}\}$. X_1, \ldots, X_n are iid, $X_j \in S$. The empirical process is

$$\mathbb{Z}_n(f) = \sqrt{n}(P_n f - P f),$$

where $P_n f = \frac{1}{n} \sum f(X_j)$. If $\mathcal{F} = \{I\{(-\infty, t]\}: t \in \mathbb{R}\}$, then

$$P_n I\{(-\infty, t]\} = F_n(t) = \frac{1}{n} \sum I\{X_j \le t\}.$$

17.1.1 Rademacher process

Let $\varepsilon_1, \ldots, \varepsilon_n$ be iid Rademacher random variables, i.e. fair coin flips $\varepsilon_j \in \{\pm 1\}$. Assume that ε_j and X_j are jointly independent. The Rademacher process is

$$R_n(f) = \frac{1}{n} \sum \varepsilon_j f(X_j) = \frac{1}{n} \langle \vec{\varepsilon}, f(\vec{X}) \rangle.$$

It is sub-Gaussian conditioned on the X_j .

Theorem 1. Symmetrization inequality, E. Giné and J. Zinn

$$\mathbb{E}||P_n - P||_{\mathcal{F}} \le 2\mathbb{E}||R_n||_{\mathcal{F}}, \quad \text{where}$$

$$||P_n - P||_{\mathcal{F}} = \sup_{f \in \mathcal{F}} |\frac{1}{n} \sum_{j} f(X_j) - \mathbb{E}f(X_j)|$$

$$||R_n||_{\mathcal{F}} = \sup_{f \in \mathcal{F}} |\frac{1}{n} \sum_{j} \varepsilon_j f(X_j)| = |\frac{1}{\sqrt{n}}||\mathbb{Z}_n(f)||.$$

Proof: Let Y_1, \ldots, Y_n be iid copies of X_1, \ldots, X_n which are jointly independent of X_j . The X_j live in California, the Y_j are born on Jupiter. Note that

$$Pf = \mathbb{E}f(X_1) = \mathbb{E}f(Y_1) = \frac{1}{n} \sum \mathbb{E}f(Y_j).$$

Then

$$\mathbb{E}\sup_{f}|P_{n}f - Pf| = \mathbb{E}\sup_{f}|P_{n}f - \tilde{\mathbb{E}}\tilde{P}_{n}f|,$$

where the \sim denotes expectation with respect to Y_i . By Jensen's inequality,

$$\mathbb{E}\sup_{f}|P_nf - \tilde{\mathbb{E}}\tilde{P}_nf| \le \mathbb{E}\tilde{\mathbb{E}}\sup_{f}|P_nf - \tilde{P}_nf|.$$

To apply Jensen's, define $Q(f) = P_n f - \tilde{P}_n f$ and $G(Q) = \sup_{f \in \mathcal{F}} |Q(f)|$; G is convex. Then

$$\mathbb{E}||P_n - P||_{\mathcal{F}} \le \mathbb{E}_{X,Y}||P_n f - \tilde{P}_n f||_{\mathcal{F}} = \mathbb{E}\sup_{f} |\frac{1}{n}\sum_{f} (f(X_j) - f(Y_j))|.$$

For any (deterministic) sequence $\sigma_j \in \{\pm 1\}, j = 1, \dots, n$,

$$\mathbb{E}\sup_{f} \left| \frac{1}{n} \sum_{j} (f(X_j) - f(Y_j)) \right| = \mathbb{E}\sup_{f} \left| \frac{1}{n} \sum_{j} \sigma_j (f(X_j) - f(Y_j)) \right|.$$

There are 2^n possible such sequences so the average is

$$2^{-n} \sum_{\sigma_j} \mathbb{E} \sup_{f \in \mathcal{F}} \left| \frac{1}{n} \sum_{\sigma_j} (f(X_j) - f(Y_j)) \right| = \mathbb{E}_{\varepsilon} \mathbb{E}_{X,Y} \sup_{f} \left| \frac{1}{n} \sum_{\sigma_j} \varepsilon_j (f(X_j) - f(Y_j)) \right|$$

$$\leq \mathbb{E}_{\varepsilon,X} \sup_{f} \left| \frac{1}{n} \sum_{\sigma_j} \varepsilon_j f(X_j) + \mathbb{E}_{\varepsilon,Y} \sup_{f} \left| \frac{1}{n} \sum_{\sigma_j} \varepsilon_j f(Y_j) \right| = 2\mathbb{E} ||R_n||_{\mathcal{F}}$$

Theorem 2. Desymmetrization inequality.

$$\mathbb{E}||P_n - P||_{\mathcal{F}} \ge \frac{1}{2}\mathbb{E}||R_n||_{\mathcal{F}_c} = \frac{1}{2}\mathbb{E}\sup_{f \in \mathcal{F}} |\frac{1}{n}\sum \varepsilon_j(f(X_j) - \mathbb{E}f(X_j))|$$

where $\mathcal{F}_c = \{f - Pf, f \in \mathcal{F}\}.$

We also have that $\mathbb{E}||R_n||_{\mathcal{F}_c} \geq \mathbb{E}||R_n||_{\mathcal{F}} - k$. WHAT'S k INDEED

$$|\frac{1}{n}\sum \varepsilon_j(f(X_j) - Pf)| \ge \frac{1}{n}\sum \varepsilon f(X_j)| - |\frac{1}{n}Pf\sum \varepsilon|$$

$$\mathbb{E}\sup_{f\in\mathcal{F}}|\frac{1}{n}\sum \varepsilon_j Pf| \le \sup_{f\in\mathcal{F}}|Pf|\mathbb{E}|\frac{1}{n}\sum \varepsilon_j| \le \sup_{f\in\mathcal{F}}|Pf|\mathbb{E}^{1/2}(\frac{1}{n}\sum \varepsilon_j)^2 = \sup_{f}|P_f|/\sqrt{n}.$$

so we can take $k = \frac{1}{\sqrt{n}} \sup_{f \in \mathcal{F}} |Pf|$.

We wish to understand this empirical bound for \mathcal{F} the class of indicator functions. Let \mathcal{C} be a collection of subsets of S. Then

$$||P_n - P||_{\mathcal{C}} := ||P_n - P||_{\mathcal{F}_{\mathcal{C}}},$$

where $\mathcal{F}_{\mathcal{C}}$ is the set of indicator functions on $C \in \mathcal{C}$.

Recall that if x_t is a process indexed by a finite set T, and $x_t \sim SG(\sigma_t^2)$, then

$$\mathbb{E}\sup_{t}|X_{t}| \leq \sqrt{2}\max_{t}\sigma_{t}\sqrt{\log(2N)}.$$

Consider $X_t = \sum t_j \varepsilon_j$, where $t = (t_1, \dots, t_n) \in \mathbb{R}^n$ and ε_j are Rademacher r.v.s. Then $X_t \in SG(||t||_2^2)$. Let $T \subset \mathbb{R}^n$ be finite with cardinality N. Then

$$R_n(T) = \sup_{t \in T} |\sum_{i \in T} \varepsilon_i t_i|,$$

$$\mathbb{E}R_n(T) \le \sqrt{2} \max_{t} ||t||_2 \sqrt{\log(2 \operatorname{card}(T))}.$$