Spring 2018: STA 6448 Advanced Probability and Inference II Lecture 7

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Uniform laws of large numbers

Rademacher complexity

For any fixed collection $x_1^n = (x_1, \dots, x_n)$ of points, consider the subset of \mathbb{R}^n given by

$$\mathcal{F}(x_1^n) = \Big\{ \big(f(x_1), \dots, f(x_n) \big) \ \Big| \ f \in \mathcal{F} \Big\}.$$

Recall that the Ramemacher complexity of this set (rescaled by n^{-1}) is defined by

$$\mathcal{R}\big(\mathcal{F}(x_1^n)/n\big) = \mathbb{E}_{\varepsilon}\Big[\sup_{f\in\mathcal{F}}\Big|\frac{1}{n}\sum_{i=1}^n\varepsilon_i f(x_i)\Big|\Big],$$

which is called the empirical Rademacher complexity.

Definition

Given random samples $X_1^n = (X_1, \dots, X_n)$, the Rademacher complexity of the function class \mathcal{F} is defined as

$$\mathcal{R}_n(\mathcal{F}) = \mathbb{E}_X \big[\mathcal{R} \big(\mathcal{F}(x_1^n)/n \big) \big] = \mathbb{E}_{X,\,\varepsilon} \Big[\sup_{f \in \mathcal{F}} \Big| \frac{1}{n} \sum_{i=1}^n \varepsilon_i f(X_i) \Big| \Big].$$

A uniform law via Rademacher complexity

Rademacher complexity characterizes the typical largest correlation between a random noise vector and any function in the class \mathcal{F} , thereby the "complexity" of \mathcal{F} .

Theorem

Let \mathcal{F} be a class of functions $f: \mathcal{X} \to \mathbb{R}$ that is uniformly bounded by b > 0. Then for all n > 0 and $\delta \ge 0$, we have

$$\|\mathbb{P}_n - \mathbb{P}\|_{\mathcal{F}} \le 2 \,\mathcal{R}_n(\mathcal{F}) + \delta$$

with \mathbb{P} probability at least $1-2 \exp\left(-\frac{n\delta^2}{8b^2}\right)$. Consequently, $\mathcal{R}_n(\mathcal{F}) = o(1)$ implies \mathcal{F} to be Glivenko-Cantelli.

Proof step one: Concentration around mean

Consider the function

$$G(x_1,\ldots,x_n) = \sup_{f\in\mathcal{F}} \left|\frac{1}{n}\sum_{i=1}^n f(x_i)\right|.$$

It satisfies the bounded difference property: for all $x_1, \ldots, x_n, x_k' \in \mathbb{R}$,

$$|G(x_1,\ldots,x_n)-G(x_1,\ldots,x_{k-1},x'_k,x_{k+1},\ldots,x_n)| \leq \frac{2\|f\|_{\infty}}{n} \leq \frac{2b}{n}.$$

Therefore, the bounded difference inequality implies the following holds with probability at least $1-2\exp\left(-\frac{n\,t^2}{8b^2}\right)$,

$$\Big| \big| \| \mathbb{P}_n - \mathbb{P} \|_{\mathcal{F}} - \mathbb{E}[\| \mathbb{P}_n - \mathbb{P} \|_{\mathcal{F}}] \Big| \leq t, \quad \text{for any } t > 0.$$

Proof step two: Upper bound on mean

Applying the symmetrization technique.

Let (Y_1, \ldots, Y_n) be a second independent copy of (X_1, \ldots, X_n) . Then

$$\mathbb{E}[\|\mathbb{P}_n - \mathbb{P}\|_{\mathcal{F}}] = \mathbb{E}_X \left[\sup_{f \in \mathcal{F}} \left| \frac{1}{n} \sum_{i=1}^n \left\{ f(X_i) - \mathbb{E}_{Y_i}[f(Y_i)] \right\} \right| \right]$$

$$= \mathbb{E}_X \left[\sup_{f \in \mathcal{F}} \left| \mathbb{E}_Y \left[\frac{1}{n} \sum_{i=1}^n \left\{ f(X_i) - f(Y_i) \right\} \right] \right| \right]$$

$$\leq \mathbb{E}_{X,Y} \left[\sup_{f \in \mathcal{F}} \left| \frac{1}{n} \sum_{i=1}^n \left\{ f(X_i) - f(Y_i) \right\} \right| \right],$$

where the last step is due to Jensen's inequality.

Proof step two: Upper bound on mean

Let ε_i be i.i.d. Rademacher random variables.

For any $f\in\mathcal{F}$, random variable $\varepsilon_i(f(X_i)-f(Y_i))$ has the same distribution as $f(X_i)-f(Y_i)$. Consequently,

$$\mathbb{E}[\|\mathbb{P}_n - \mathbb{P}\|_{\mathcal{F}}] \leq \mathbb{E}_{X,Y} \Big[\sup_{f \in \mathcal{F}} \Big| \frac{1}{n} \sum_{i=1}^n \varepsilon_i \Big\{ f(X_i) - f(Y_i) \Big\} \Big| \Big]$$

$$\leq 2\mathbb{E}_{X,\varepsilon} \Big[\sup_{f \in \mathcal{F}} \Big| \frac{1}{n} \sum_{i=1}^n \varepsilon_i f(X_i) \Big| \Big] = 2\mathcal{R}_n(\mathcal{F}).$$

Necessary conditions with Rademacher complexity

In the proof, we relates $\|\mathbb{P}_n - \mathbb{P}\|_{\mathcal{F}}$ with its symmetrized version

$$||R_n||_{\mathcal{F}} = \sup_{f \in \mathcal{F}} \left| \frac{1}{n} \sum_{i=1}^n \varepsilon_i f(X_i) \right|.$$

The stochastic process R_n over \mathcal{F} is known as the Rademacher process. What is lost in moving from $\|\mathbb{P}_n - \mathbb{P}\|_{\mathcal{F}}$ to $\|R_n\|_{\mathcal{F}}$? Essentially nothing!

Theorem

For any convex non-decreasing function $\Phi: \mathbb{R} \to \mathbb{R}$, we have

$$\mathbb{E}_{X,\varepsilon}\left[\Phi\left(\frac{1}{2}\|R_n\|_{\bar{\mathcal{F}}}\right)\right] \leq \mathbb{E}[\|\mathbb{P}_n - \mathbb{P}\|_{\mathcal{F}}] \leq \mathbb{E}_{X,\varepsilon}\left[\Phi\left(2\|R_n\|_{\mathcal{F}}\right)\right],$$

where $\bar{\mathcal{F}} = \{f - \mathbb{E}[f] : f \in \mathcal{F}\}$ is the re-centered function class.

Necessary conditions with Rademacher complexity

Corollary

Let \mathcal{F} be a class of functions $f:\mathcal{X}\to\mathbb{R}$ that is uniformly bounded by b>0. Then for all n>0 and $\delta\geq 0$, we have

$$\|\mathbb{P}_n - \mathbb{P}\|_{\mathcal{F}} \ge \frac{1}{2} \, \mathcal{R}_n(\mathcal{F}) - \frac{b}{2\sqrt{n}} - \delta$$

with \mathbb{P} probability at least $1-2 \exp\left(-\frac{n\delta^2}{8b^2}\right)$.

Combined with the previous result, we obtain a two sided bound: with probability at least $1-2 \exp\left(-\frac{n\delta^2}{8b^2}\right)$,

$$\frac{1}{2}\,\mathcal{R}_n(\mathcal{F}) - 2\delta \leq \|\mathbb{P}_n - \mathbb{P}\|_{\mathcal{F}} \leq \mathcal{R}_n(\mathcal{F}) + \delta, \ \text{ for all } \delta > 0.$$

Some upper bounds on Rademacher complexity

Given $x_1^n = (x_1, \dots, x_n)$, the size of

$$\mathcal{F}(x_1^n) = \{(f(x_1), \dots, f(x_n)) : f \in \mathcal{F}\}\$$

provides a sample-dependent measure of the complexity of $\ensuremath{\mathcal{F}}.$

Definition

For a class $\mathcal{F} \subset \{0,1\}^{\mathcal{X}}$, the growth function is

$$\Pi_{\mathcal{F}}(n) = \max \{ |\mathcal{F}(x_1^n)| : x_1, \dots, x_n \in \mathcal{X} \}.$$

A class ${\mathcal F}$ is said to have polynomial growth of order $\nu \geq 1$ if

$$\Pi_{\mathcal{F}}(n) \leq (n+1)^{\nu}$$
, for all $n \geq 1$.

Controlling Rademacher complexity: growth function

Theorem

For any $x_1^n=(x_1,\ldots,x_n)$, let $D(x_1^n)=\sup_{f\in\mathcal{F}}\sqrt{\frac{\sum_{i=1}^nf^2(x_i)}{n}}$ denote the ℓ_2 radius of $\mathcal{F}(x_1^n)/\sqrt{n}$. Then

$$\mathcal{R}(\mathcal{F}(x_1^n)/n) = \mathbb{E}_{\varepsilon} \Big[\sup_{f \in \mathcal{F}} \Big| \frac{1}{n} \sum_{i=1}^n \varepsilon_i f(x_i) \Big| \Big] \leq D(x_1^n) \sqrt{\frac{2 \log(2 \prod_{\mathcal{F}}(n))}{n}}.$$

In particular, if $\mathcal F$ is uniformly bounded by b>0, and has polynomial growth of order $\nu\geq 1$, then

$$\mathcal{R}_n(\mathcal{F}) \le b \sqrt{\frac{2\nu \log(2(n+1))}{n}}.$$

Proof is left as a homework problem.

Application: Classical Glivenko-Cantelli theorem

Recall the classical Glivenko-Cantelli theorem on the uniform convergence of CDFs:

$$\|\widehat{F}_n - F\|_{\infty} \stackrel{\text{a.s.}}{\to} 0,$$

Corollary

Let F be the cdf and \widehat{F}_n the empirical CDF, then

$$\mathbb{P}\Big[\|\widehat{F}_n - F\|_{\infty} \ge \sqrt{\frac{2\log(2(n+1))}{n}} + \delta\Big] \le 2e^{-\frac{n\delta^2}{8}} \quad \text{for all } \delta > 0,$$

and hence $\|\widehat{F}_n - F\|_{\infty} \stackrel{a.s.}{\to} 0$.

Proof: Take $\mathcal{F} = \{(-\infty, t] : t \in \mathbb{R}\}$, then \mathcal{F} is uniformly bounded by 1, and has polynomial growth of order 1.

The bound is not tight (the log(n + 1) factor can be removed).

Vapnik-Chervonenkis (VC) dimension

Definition

A class $\mathcal{F} \subset \{0,1\}^{\mathcal{X}}$ shatters $(x_1,\ldots,x_d) \subset \mathcal{X}$ means $|\mathcal{F}(x_1^d)| = 2^d$.

The VC-dimension $d_{VC}(\mathcal{F})$ is defined as the largest integer d for which there is some $(x_1,\ldots,x_d)\subset\mathcal{X}$ of d points that can be shattered by \mathcal{F} .

Examples

- ▶ $\mathcal{F}_{left} = \{(-\infty, t] : t \in \mathbb{R}\}$ has VC-dim 1. It has polynomial growth of order 1.
- ▶ $\mathcal{F}_{two} = \{(s, t] : s, t \in \mathbb{R}\}$ has VC-dim 2. It has polynomial growth of order 2 (why?).

Vapnik-Chervonenkis (VC) dimension

Theorem (Sauer's Lemma)

If $d_{VC}(\mathcal{F}) \leq d$, then

$$\Pi_{\mathcal{F}}(n) \leq \sum_{k=1}^{d} \binom{n}{k} \leq (n+1)^d.$$

Consequently, if $d_{VC}(\mathcal{F}) < \infty$ (called VC class), then \mathcal{F} has polynomial growth of order $d_{VC}(\mathcal{F})$.

Proof: See "Weak convergence and empirical processes: with applications to statistics", Section 2.6.1.

Some useful results on Rademacher complexity

Properties

- 1. $\mathcal{F}_1 \subset \mathcal{F}_2$ implies $\mathcal{R}_n(\mathcal{F}_1) \leq \mathcal{R}_n(\mathcal{F}_2)$.
- 2. For any constant $c \in \mathbb{R}$, $\mathcal{R}_n(c \mathcal{F}) = |c| \mathcal{R}_n(\mathcal{F})$.
- 3. For any fixed bounded function g (bounded by b), $|\mathcal{R}_n(\mathcal{F}+g)-\mathcal{R}_n(\mathcal{F})| \leq b \sqrt{2\log 2/n}$.
- 4. $\mathcal{R}_n(\mathsf{conv}(\mathcal{F})) = \mathcal{R}_n(\mathcal{F})$, where $\mathsf{conv}(\mathcal{F})$ is the convex hull of \mathcal{F} .
- 5. If $\phi: \mathbb{R} \to \mathbb{R}$ is 1-Lipschitz continuous and satisfies $\phi(0) = 0$, then $\mathcal{R}(\phi(\mathcal{F})) \leq 2\mathcal{R}(\mathcal{F})$.

For a proof of the last claim, see "Probability in Banach Spaces" by Michel Ledoux and Michel Talagrand, Theorem 4.12.