36-755: Advanced Statistical Theory I

Lecture 16: October 24

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16.1 A uniform law via Rademacher complexity

16.1.1 Classes with polynomial discrimination

Recall if \mathcal{F} is a class of functions that are uniformly bounded by b > 0, then we have

$$\mathbb{P}\left(||P_n - P||_{\mathcal{F}} \ge 2\mathcal{R}_n(\mathcal{F}) + t\right) \le \exp\left(-\frac{nt^2}{2b^2}\right)$$

where

$$\mathcal{R}_{n}(\mathcal{F}) = \mathbb{E}_{X,\epsilon} \left[\sup_{f \in \mathcal{F}} \left| \frac{1}{n} \sum_{i=1}^{n} \epsilon_{i} f(X_{i}) \right| \right] \quad \text{and} \quad ||P_{n} - P||_{\mathcal{F}} = \sup_{f \in \mathcal{F}} \left| \frac{1}{n} \sum_{i=1}^{n} \left(f(X_{i}) - \mathbb{E}\left[f(X_{i}) \right] \right) \right|.$$
(16.1)

To bound $\mathcal{R}_n(\mathcal{F})$, we will use the VC theory and later we will develop more general tools.

Remark 16.1 (Concentration property of Rademacher complexity) Let $g : \mathbb{R} \to \mathbb{R}$ such that $|g(x) - g(y)| \le L|x-y|$, g(0) = 0 and set $g \circ \mathcal{F} = \{g \circ f, f \in \mathcal{F}\}$. Then

$$\mathcal{R}_n(g \circ \mathcal{F}) \le 2L\mathcal{R}_n(\mathcal{F}).$$

Example 16.2 Suppose the function $f(x) = x^2$ is defined on [-L, L]. Then,

$$\mathbb{E}_{X,\epsilon}\left[\sum_{f\in\mathcal{F}}\frac{1}{n}\Big|\sum_{i=1}^{n}\epsilon_{i}f^{2}(X_{i})\Big|\right] \leq 4L\mathbb{E}_{X,\epsilon}\left[\sum_{f\in\mathcal{F}}\frac{1}{n}\Big|\sum_{i=1}^{n}\epsilon_{i}f(X_{i})\Big|\right].$$

Definition 16.3 (Polynomial discrimination) A class \mathcal{F} of functions defined on the domain \mathcal{X} such that $\mathcal{F} = \{f : \mathcal{X} \to \mathcal{R}\}$ has polynomial discrimination with parameter $\nu \geq 1$ if for each positive integer n and collection $x_1^n = \{x_1, \dots, x_n\}$ of n points in \mathcal{X} , the set

$$\mathcal{F}(x_1^n) = \{ (f(x_1), \cdots, f(x_n)) \in \mathbb{R}^n, f \in \mathcal{F} \}$$

has cardinality upper bounded as

$$|\mathcal{F}(x_1^n)| \le (n+1)^{\nu}.$$

Lemma 16.4 If \mathcal{F} has polynomial discrimination with parameter ν , then for all n and any x_1^n , we have

$$\mathbb{E}_{\epsilon}\left[\sup_{f\in\mathcal{F}}\frac{1}{n}\Big|\sum_{i=1}^{n}\epsilon_{i}f(x_{i})\Big|\right] \leq D(x_{1}^{n})\sqrt{\frac{\nu\log(n+1)}{n}}$$

where $D(x_1^n) = \sup_{f \in \mathcal{F}} \sqrt{\frac{\sum_{i=1}^n f^2(x_i)}{n}}$.

Corollary 16.5 As a corollary, we obtain the following results.

1)
$$\mathcal{R}_n(\mathcal{F}) \leq 2\mathbb{E}_X \left[D(x_1^n) \right] \sqrt{\frac{\nu \log(n+1)}{n}}$$

2) If $||f||_{\infty} = \sup_{x \in \mathcal{X}} |f(x)| < b$ for all $f \in \mathcal{F}$, then $\mathcal{R}_n(\mathcal{F}) \leq 2b\sqrt{\frac{\nu \log(n+1)}{n}}$.

16.1.2 Uniform convergence of CDFs

Consider the function class $\mathcal{F} = \{(-\infty, t] : t \in \mathbb{R}\}$. In this case, $||P_n - P||_{\mathcal{F}}$ defines the Kolmogorov-Smirnov statistic as

$$||P_n - P||_{\mathcal{F}} = \sup_t \left| \hat{F}_n(t) - F(t) \right|.$$

Note that for a fixed $x_1^n = (x_1, \cdots, x_n) \in \mathbb{R}^n$, the ordered samples

$$x_{(1)} \le x_{(2)} \le \dots \le x_{(n-1)} \le x_{(n)}$$

split the real line into at most n + 1 intervals including $(-\infty, x_{(1)}]$ and $(x_{(n)}, \infty]$ and for a given t, the indicator function $I_{[t,\infty)}$ takes the value 1 for all $x_{(i)} \ge t$, and 0 for all other samples. It follows that for any given sample x_1^n , we have $|\mathcal{F}(x_1^n)| \le n+1$ and \mathcal{F} has polynomial discrimination with $\nu = 1$. Consequently, we can show a quantitative version of Glivenko-Cantelli theorem as follows.

Corollary 16.6 (Classical Glivenko-Cantelli) Let $F(t) = \mathbb{P}(X \leq t)$ be the CDF of a random variable X, and let $\hat{F}_n(t)$ be the empirical CDF based on n i.i.d. samples $X_i \sim \mathbb{P}$. Then,

$$\mathbb{P}\left(||\hat{F}_n - F||_{\infty} \ge 4\log\sqrt{\frac{\log(n+1)}{n}} + t\right) \le \exp\left(-\frac{nt^2}{2}\right)$$

for all $t \geq 0$, and hence $||\hat{F}_n - F||_{\infty} \stackrel{a.s.}{\to} 0$.

Proof: The claim follows from Eq. (16.1) and Corollary 16.5.

Dvoretzky-Kiefer-Wolfowitz (DKW) inequality provides a shaper tail bound of $||\hat{F}_n - F||_{\infty}$ as

$$\mathbb{P}\left(||\hat{F}_n - F||_{\infty} > t\right) \le 2\exp\left(-\frac{nt^2}{2}\right)$$

for every t > 0.

16.2 Vapnik-Chervonenkis (VC) dimension

Let us assume \mathcal{F} is a collection of $\{0,1\}$ functions and represent this class using the collection \mathcal{A} of subsets in \mathcal{X} as follows.

$$f \in \mathcal{F} \iff \mathcal{A} = \{x \in \mathcal{X} : f(x) = 1\}$$

Then, for a fixed x_1^n , we have

$$\mathcal{F}(x_1^n) = \mathcal{A}(x_1^n) = \{A \cap x_1^n : A \in \mathcal{A}\}.$$

Clearly, we can see that $|\mathcal{A}(x_1^n)| \leq 2^n$. A VC-class of sets is a class such that $|\mathcal{A}(x_1^n)|$ grows only polynomially in n.

Definition 16.7 (Shattering and VC dimension) The class \mathcal{A} shatters the n-tuple x_1^n if $|\mathcal{A}(x_1^n)| = 2^n$. The VC-dimension ν of \mathcal{A} is the largest n such that some n-tuple x_1^n is shattered by \mathcal{A} .

If $n > \nu$, then no *n*-tuple x_1^n is shattered by \mathcal{A} .

Example 16.8 Here are two typcial examples.

- For $\mathcal{A} = \{(-\infty, x] : x \in \mathbb{R}\}$, the VC-dimension of \mathcal{A} is $\nu(\mathcal{A}) = 1$.
- For $\mathcal{A} = \{(b, a] : b < a\}$, the VC-dimension of \mathcal{A} is $\nu(\mathcal{A}) = 2$.

If the VC dimension is finite, then the growth function cannot grow too quickly.

Lemma 16.9 (Sauer's lemma) Suppose \mathcal{A} has the finite VC-dimension $\nu_{\mathcal{A}}$. Then for $n \geq \nu_{\mathcal{A}}$,

$$\max_{x_1^n} |\mathcal{A}(x_1^n)| \le \sum_{i=0}^{\nu_{\mathcal{A}}} \binom{n}{i} \le (n+1)^{\nu_{\mathcal{A}}}.$$

Let $\mathcal{S}_{\mathcal{A}}(n)$ be the shattering coefficient, $\max_{x_1^n} |\mathcal{A}(x_1^n)|$. Then, Lemma 16.9 provides the following inequality.

$$\mathcal{R}_n(\mathcal{F}) \le \sqrt{\frac{2\log \mathcal{S}_{\mathcal{A}}(2n)}{n}} \le \sqrt{\frac{4\nu_{\mathcal{A}}\log n}{n}}$$

16.3 Controlling the VC-dimension

16.3.1 Basic operations

Let \mathcal{A} and \mathcal{B} be two collections of subsets in $\mathcal{X}(=\mathbb{R}^d)$. Then,

- 1. $\mathcal{S}_{\mathcal{A}}(n) = \mathcal{S}_{\mathcal{A}^C}(n).$
- 2. If $A \cup B = \{A \cup B : A \in \mathcal{A}, B \in \mathcal{B}\}$, then

$$\mathcal{S}_{A\cup B}(n) \leq \mathcal{S}_{\mathcal{A}}(n)\mathcal{S}_{\mathcal{B}}(n).$$

3. The same bound holds for

$$A \cap B = \{A \cap B : A \in \mathcal{A}, B \in \mathcal{B}\}$$
$$A \times B = \{A \times B : A \in \mathcal{A}, B \in \mathcal{B}\}$$

4. $\mathcal{S}_{\mathcal{A}}(n+m) \leq \mathcal{S}_{\mathcal{A}}(n)\mathcal{S}_{\mathcal{A}}(m).$

5. If $C = A \cup B$, then

$$\mathcal{S}_{\mathcal{C}}(n) \leq \mathcal{S}_{\mathcal{A}}(n) + \mathcal{S}_{\mathcal{B}}(n).$$

More examples are provided as

- 1. If $\mathcal{A} = \{(-\infty, x_1] \times \cdots \times (-\infty, x_n] : (x_1, \cdots, x_d) \in \mathbb{R}^d\}$, then $\nu_{\mathcal{A}} = d$.
- 2. Let \mathcal{A} be the set of all rectangles in \mathbb{R}^d . Then, $\nu_{\mathcal{A}} = 2d$.

16.3.2 Vector space structure

Proposition 16.10 Let \mathcal{G} be a finite dimensional vector space of real-valued functions on \mathbb{R}^d . Then, the class

$$\mathcal{A} = \{\{x : g(x) \le 0\}, \forall g \in \mathcal{G}\}$$

has VC dimension at most $dim(\mathcal{G})$.

Example 16.11 (Spheres in \mathbb{R}^d) Consider the sphere

$$\mathcal{A} = \{ \mathbb{B}(x, r) : x \in \mathbb{R}^d, r > 0 \} \text{ where } \mathbb{B}(x, r) = \{ y : ||x - y||^2 \le r^2 \}.$$

Then, $\nu_{\mathcal{A}} \leq d+2$.

Proof: Notice that $\forall x \in \mathbb{R}^d$ and r > 0,

$$f_{r,y}(x) = \sum_{i=1}^{d} (x_i - y_i)^2 - r^2$$

= $\sum_{i=1}^{d} x_i^2 + \sum_{i=1}^{d} y_i^2 - 2\sum_{i=1}^{d} x_i y_i - r^2 \le 0.$

We first define a feature map $\phi : \mathbb{R}^d \to \mathbb{R}^{d+2}$ via $\phi(x) = (1, x_1, \cdots, x_d, ||x||_2^2)$. Then, consider functions of the form

$$g_c(x) = c^T \phi(x)$$
 where $c \in \mathbb{R}^{d+2}$.

The family of functions $\{g_c, c \in \mathbb{R}^{d+2}\}$ is a vector space of dimension d+2, and it contains the function class $f_{r,y}(x)$. Then, the result follows by Proposition 16.10.