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SDS 384 11: Theoretical Statistics

Lecture 15: Uniform Law of Large Numbers-Rademacher and Gaussian Complexity

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A parametric class

Example

For any fixed θ, define the real-valued function $f_\theta(x) := 1 \exp(-\theta|x|)$, and consider the function class

$$\mathcal{F} = \{f_\theta : [0,1] \to \mathcal{R} | \theta \in [0,1]\}$$

Using the uniform norm as a metric, i.e.

$\|f - g\|_\infty := \sup_{x \in [0,1]} |f(x) - g(x)|$. Prove that

$$\lfloor \frac{1 - 1/e}{2\delta} \rfloor + 1 \leq N(\delta; \mathcal{F}, \|.\|_\infty) \leq \frac{1}{2\delta} + 2.$$

Proof-upper bound

- First note that $|f(\theta) - f(\theta')| \leq |\theta - \theta'|$
- For any $\delta \in (0, 1)$, let $T = \lfloor \frac{1}{2\delta} \rfloor$
- Consider $S = \{\theta^0, \ldots, \theta^{T+1}\}$ where $\theta^i = 2\delta i$ for $i \leq T$ and $\theta^{T+1} = 1$.
- $\{f_{\theta^i} : \theta^i \in S\}$ is a δ cover for $\mathcal{F}$.
- For any $\theta \in [0, 1]$ we can find $\theta^i \in S$ such that $|\theta^i - \theta| \leq \delta$
- Indeed we have,

$$\begin{aligned}
\|f_{\theta^i} - f_\theta\|_\infty &= \sup_{x \in [0,1]} |\exp(-\theta^i |x|) - \exp(-\theta |x|)| \\
&\leq |\theta^i - \theta| \leq \delta
\end{aligned}$$

So $N(\delta; \mathcal{F}, \|.\|_\infty) \leq 2 + T \leq 2 + \frac{1}{\delta}$

Proof-lower bound

- We will do a δ packing.
- Let $\theta^i = -\log(1 - i\delta)$ for $i = 0, \ldots, T$
- $-\log(1 - T\delta) = 1$, and so the largest integral value is $T = \lfloor \frac{1 - 1/e}{\delta} \rfloor$
- So $M(\delta; \mathcal{F}, \|.\|_\infty) \geq 1 + \lfloor \frac{1 - 1/e}{\delta} \rfloor$
- $N(\delta; \mathcal{F}, \|.\|_\infty) \geq M(2\delta; \mathcal{F}, \|.\|_\infty) \geq 1 + \lfloor \frac{1 - 1/e}{2\delta} \rfloor$

Make a comparison

- Recall that for a L Lipschitz continuous functions supported on $[0,1]$ with $f(0)=0$, the metric entropy was L/δ
- Also recall that for a L Lipschitz continuous functions supported on $[0,1]^d$ with $f(0)=0$, the metric entropy was $(L/\delta)^d$
- However for a given function class like the last one the metric entropy is $\log(1/\delta)$
- Recall that for Unit hypercubes in d dimensions the metric entropy is $d\log(1+1/\delta)$
- Note that for Lipschitz continuous functions the dependence on d is exponential. This is a much richer class of functions, so the size is considerably larger and scales poorly with d.

A Stochastic Process

- Consider a set $\mathcal{T} \subseteq \mathcal{R}^{\boldsymbol{d}}$.
- The family of random variables $\{X_\theta : \theta \in \mathcal{T}\}$ define a Stochastic process indexed by $\mathcal{T}$.
- We are often interested in the behavior of this process given its dependence on the structure of the set $\mathcal{T}$.
- In the other direction, we want to know the structure of $\mathcal{T}$ given the behavior of this process.

Gaussian and Rademacher processes

Definition

A canonical Gaussian process is indexed by $\mathcal{T}$ is defined as:

$$G_\theta := \langle z, \theta \rangle = \sum_k z_k \theta_k,$$

where $z_k \overset{\text{iid}}{\sim} N(0,1)$. The supremum $\mathcal{G}(\mathcal{T}) := E_z[\sup_{\theta \in \mathcal{T}} G_\theta]$ is the Gaussian complexity of $\mathcal{T}$.

Rademacher complexity

- Replacing the iid standard normal variables by iid Rademacher random variables gives a Rademacher process $\{R_\theta, \theta \in \mathcal{T}\}$, where

$$R_\theta := \langle \epsilon, \theta \rangle = \sum_k \epsilon_k \theta_k, \qquad \text{where } \epsilon_k \overset{\text{iid}}{\sim} \mathit{Uniform}\{0, 1\}$$

- $\mathcal{R}(\mathcal{T}) := E_\epsilon[\sup_{\theta \in \mathcal{T}} R_\theta]$ is called the Rademacher complexity of $\mathcal{T}$.

How does this relate to the former notions of Rademacher complexity?

- Recall that
  $\mathcal{R}_{\mathcal{F}} := E[\sup_{f\in\mathcal{F}} |\sum_i \epsilon_i f(X_i)|] = E[E[\sup_{f\in\mathcal{F}} |\sum_i \epsilon_i f(X_i)||X_1, \ldots, X_n]]$

- Now the inner expectation can be upper bounded by
  $E_\epsilon \sup_{\theta\in\mathcal{T}\bigcup -\mathcal{T}} \sum_i \epsilon_i \theta_i$, where $\mathcal{T} \subseteq \mathbb{R}^n$ can be written as

$$\mathcal{T} = \{(f(X_1), \ldots, f(X_n))|f \in \mathcal{F}\}$$

Relationship

Theorem

For $\mathcal{T} \in \mathbb{R}^d$,

$$\mathcal{R}(\mathcal{T}) \leq \sqrt{\frac{\pi}{2}}\mathcal{G}(\mathcal{T}) \leq c\sqrt{\log d}\,\mathcal{R}(\mathcal{T})$$

- This is showing that there can be there are some sets where the Gaussian complexity can be substantially larger than the Rademacher complexity.
- We will in fact give an example.

Proof (of first inequality)

$$
\begin{aligned}
E[\mathcal{G}(\mathcal{T})] &= E \sup_{\theta \in \mathcal{T}} \sum_i z_i \theta_i \\
&= E \sup_{\theta \in \mathcal{T}} \sum_i \epsilon_i |z_i| \theta_i \\
&= E_\epsilon E_z \sup_{\theta \in \mathcal{T}} \sum_i \epsilon_i |z_i| \theta_i \\
&\geq E_\epsilon \sup_{\theta \in \mathcal{T}} \sum_i \epsilon_i E|z_i| \theta_i \\
&= \sqrt{\frac{2}{\pi}} \mathcal{R}(\mathcal{T})
\end{aligned}
$$

Example

Example

Consider the L_1 ball in $\mathcal{R}^d$ denoted by B_1^d.

$$\mathcal{R}(B_1^d) = 1, \mathcal{G}(B_1^d) \leq \sqrt{2 \log d}$$

- $\mathcal{R}(B_1^d) = E[\sup_{\|\theta\|_1 \leq 1} \sum_i \theta_i \epsilon_i] = E[\|\epsilon\|_\infty] = 1$
- Similarly, $\mathcal{G}(B_1^d) = E[\|z\|_\infty]$

Recall the finite class lemma?

Theorem

Consider z with independent sub-gaussian components.

$$E \max_{a \in A} < z, a > \leq \max_{a \in A} \|a\| \sqrt{2 \log |A|}$$

- In our case, $A = \{e_i, i \in [d]\}$, $|A| = d$ and $\max_{a \in A} \|a\| = 1$.

Application-Random matrix singular value

Theorem

Consider a random matrix $M = (\xi_{ij})_{i,j\in[n]}$ where ξ_{ij} are standard normal random variables.

$$P(\|M\|_{op} \geq A\sqrt{n}) \leq C\exp(-cAn)$$

where c, C are absolute constants and $A \geq C$.

- This works for symmetric wigner ensembles and hermitian matrices as well.

Operator norm

- Let $S_n := \{x \in \mathbb{R}^n : \|x\|_2 = 1\}$
- $\|M\|_{op} := \sup_{x \in \mathbb{R}^n} \|Mx\|$
- First note that we have

$$P(\|Mx\| \geq A\sqrt{n}) \leq C \exp(-cAn)$$

- This is because for each row M_i, we have

$$M_i^T x \sim Subgaussian(1), (M_i^T x)^2 - 1 \sim Subexponential(2, 4)$$

- $\|Mx\|^2 - n \sim Subexponential(2\sqrt{n}, 4)$
- So $P(\|Mx\| \geq A\sqrt{n}) \leq C \exp(-cAn)$

Can I just use an Union bound?

- Not really.
- But I can form a $1/2$ cover of S_n.