SDS 384 11: Theoretical Statistics

Lecture 12: Uniform Law of Large Numbers-Rademacher Complexity

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Proof of the GC theorem

- We will work on a proof that can handle general function classes $\mathcal{F}$ with bounded functions. WLOG let $|f(X_i)| \leq 1$ for $f \in \mathcal{F}$.

- Recall that we want to bound $\|\hat{P}_n - P\|_{\mathcal{F}}$
  $(:= \sup\limits_{f \in \mathcal{F}} |\frac{1}{n} \sum\limits_i f(X_i) - E[f]|)$

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  - Concentration inequality to bound $\|\hat{P}_n - P\|_{\mathcal{F}} - E[\|\hat{P}_n - P\|_{\mathcal{F}}]$

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  - Symmetrization to relate $E[\|\hat{P}_n - P\|_{\mathcal{F}}]$ to Rademacher complexity
  - Bound this complexity using the effective "size" of the function class.

Concentration

- First note that we cannot apply Hoeffding/Chernoff here.
- Let $X := \{X_1, \ldots, X_n\}$
- Let $g(X) = \|\hat{P}_n - P\|_{\mathcal{F}}$. Let Y be another sample $\{Y_1, \ldots, Y_n\}$, where $Y_i = X_i, \forall i \neq 1$.
- Let f_1 maximize $g(X)$, and f_2 maximize $g(Y)$
-

$$
\begin{aligned}
g(X) - g(Y) &= \left| \frac{\sum_i f_1(X_i)}{n} - Ef_1[X_1] \right| - \left| \frac{\sum_i f_2(Y_i)}{n} - Ef_2[X_1] \right| \\
&\leq \left| \frac{\sum_i f_1(X_i)}{n} - Ef_1[X_1] \right| - \left| \frac{\sum_i f_1(Y_i)}{n} - Ef_1[X_1] \right| \\
&\leq \frac{2}{n}
\end{aligned}
$$

Concentration

- Using McDiarmid's inequality, we get:

$$P\left(g(X) - E[g(X)] \geq \epsilon\right) \leq \exp(-\epsilon^2 n/2)$$

- So, with probability $1 - \exp(-\epsilon^2 n/2)$,

$$\|\hat{P}_n - P\|_{\mathcal{F}} \leq E[\|\hat{P}_n - P\|_{\mathcal{F}}] + \epsilon.$$

- So, we need to bound $E[\|\hat{P}_n - P\|_{\mathcal{F}}]$.

Symmetrization

- Consider an iid copy of X' of X

$$E\|\hat{P}_n - P\|_{\mathcal{F}} = E \sup_{f \in \mathcal{F}} \left| \frac{1}{n} \sum_i (f(X_i) - E[f(X_i)]) \right|$$

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$$= E \sup_{f \in \mathcal{F}} \left| \frac{1}{n} \sum_i (f(X_i) - E[f(X_i')]) \right|$$

$$= E_X \sup_{f \in \mathcal{F}} \left| E_{X'} \left[\frac{1}{n} \sum_i (f(X_i) - f(X_i')) \right] \right|$$

$$\leq E_{X,X'} \sup_{f \in \mathcal{F}} \left| \frac{1}{n} \sum_i (f(X_i) - f(X_i')) \right|$$

$$\leq E_{X,X'} \|\hat{P}_n - \hat{P}_n'\|_{\mathcal{F}}$$

Symmetrize again

- Let $\epsilon_i \in \{1, -1\}$.
- Note that $f(X_i) - f(X_i')$ is symmetric

Rademacher complexity

$$E\|\hat{P}_n - P\|_{\mathcal{F}} \leq E_{X,X'} \sup_{f \in \mathcal{F}} \left| \frac{1}{n} \sum_i (f(X_i) - f(X_i')) \right|$$

- $\mathcal{R}_{\mathcal{F}}$ is also called the Rademacher complexity of the function class.

Rademacher complexity

$$E\|\hat{P}_n - P\|_{\mathcal{F}} \leq E_{X,X'} \sup_{f \in \mathcal{F}} \left| \frac{1}{n} \sum_i (f(X_i) - f(X_i')) \right|$$

$$= E_{X,X',\epsilon} \sup_{f \in \mathcal{F}} \left| \frac{1}{n} \sum_i \epsilon_i (f(X_i) - f(X_i')) \right|$$

$$\leq E_{X,\epsilon} \sup_{f \in \mathcal{F}} \left| \frac{1}{n} \sum_i \epsilon_i f(X_i) \right| + E_{X',\epsilon} \sup_{f \in \mathcal{F}} \left| \frac{1}{n} \sum_i \epsilon_i f(X_i')) \right|$$

$$= 2E \sup_{f \in \mathcal{F}} \left| \frac{1}{n} \sum_i \epsilon_i f(X_i) \right| =: 2\mathcal{R}_{\mathcal{F}}$$

Why the Rademacher complexity?

- We have now shown that $\|\hat{P}_n - P\|_{\mathcal{F}} \leq 2\mathcal{R}_{\mathcal{F}} + \epsilon$ with prob. $1 - e^{-n\epsilon^2/2}$.

- $\mathcal{R}_{\mathcal{F}}$ measures the maximum possible correlation (over all $f \in \mathcal{F}$) between the vector $(f(X_1), \ldots, f(X_n))$ and the "noise vector" $(\epsilon_1, \ldots, \epsilon_n)$.

- If a function class has some function which has a high correlation with a random noise vector, then we should not expect concentration.

- If $\mathcal{R}_n$ is $o(1)$ then the Borel Cantelli lemma gives $\|\hat{P}_n - P\|_{\mathcal{F}} \overset{a.s.}{\to} 0$.

Size of a function class $\mathcal{F}$

- Let $\mathcal{F}(X) = \{(f(X_1), \ldots, f(X_n)) : f \in \mathcal{F}\}$

- $\mathcal{R}_\mathcal{F} = E \sup_{f \in \mathcal{F}} \left| \frac{1}{n} \sum_i \epsilon_i f(X_i) \right| = E \left[E \sup_{f \in \mathcal{F}} \left| \frac{1}{n} \sum_i \epsilon_i f(X_i) \right| \middle| X_1, \ldots, X_n \right]$

- In the next slide we will bound this using the cardinality of $\mathcal{F}(X)$

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Theorem

Let $A \subseteq \mathbb{R}^n$, $R = \max_{a \in A} \|a\|$,

$$E \sup_{a \in A} \langle \epsilon, a \rangle \leq \sqrt{2R^2 \log |A|}.$$

And,

$$E \sup_{a \in A} |\langle \epsilon, a \rangle| \leq \sqrt{2R^2 \log |2A|}.$$

Proof

Proof.

$$\exp\left(\lambda E \sup_{a \in A} \langle \epsilon, a \rangle\right) \leq E \exp\left(\lambda \sup_{a \in A} \langle \epsilon, a \rangle\right)$$

$$= E \sup_{a \in A} \exp\left(\lambda \langle \epsilon, a \rangle\right)$$

$$\leq \sum_{a \in A} E \exp\left(\lambda \langle \epsilon, a \rangle\right)$$

$$(\langle \epsilon, a \rangle \sim \mathsf{Subgaussian}(\|a\|_2^2)) \quad \leq \sum_{a \in A} \exp\left(\frac{\lambda^2 \|a\|_2^2}{2}\right)$$

$$\leq |A| \exp\left(\frac{\lambda^2 R^2}{2}\right)$$

Take $\lambda = 2 \log |A| / R^2$. $\qquad \square$

- Note that in this case $\mathcal{A}$ contains of vectors $(f(X_1)/n, \ldots, f(X_n)/n)$, where f is a indicator function, i.e. $f(X_i) = 1(X_i \leq t)$.
- So $R^2 = 1/n$.

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- So $R^2 = 1/n$.

- The question is for a given dataset $X_1, \ldots X_n$, how many distinct points are there in $\mathcal{A}$?

$$\begin{aligned}
|\mathcal{A}| = |\mathcal{F}(X)| &= |\{(f(X_{(1)}), \ldots, f(X_{(n)})) : f \in \mathcal{F}\}| \\
&= |\{(1(X_{(1)} \leq t), \ldots, 1(X_{(n)} \leq t)) : t \in \mathbb{R}\}| \\
&\leq n + 1 \qquad \text{(HUH!!)}
\end{aligned}$$

Glivenko Cantelli

Proof.

If $\mathcal{F}$ is the set of one sided indicator functions, then

$$\|\hat{P}_n - P\|_{\mathcal{F}} \le 2\mathcal{R}_{\mathcal{F}} + \epsilon = 2E[E[\sup_{f \in \mathcal{F}} \sum_i \epsilon_i f(X_i)/n]|X] + \epsilon$$

$$\le \sqrt{8R^2 \log(n+1)} + \epsilon$$

$$\le \sqrt{\frac{8\log(n+1)}{n}} + \epsilon$$

By Borel Cantelli, $\|\hat{P}_n - P\|_{\mathcal{F}} \overset{a.s.}{\to} 0$ $\qquad\qquad\square$