

# 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 F
  with bounded functions. WLOG let |f(X<sub>i</sub>)| ≤ 1 for f ∈ F.
- ullet Recall that we want to bound  $\|\hat{P}_n P\|_{\mathcal{F}}$
- The proof has three components:
  - Concentration inequality to bound  $\|\hat{P}_n P\|_{\mathcal{F}} E[\|\hat{P}_n P\|_{\mathcal{F}}]$
  - 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  $X := \{X_1, \dots, X_n\}$
- Let  $g(X) = \|\hat{P}_n P\|_{\mathcal{F}}$ . Let Y be another sample  $\{Y_1, \dots, Y_n\}$ , where  $Y_i = X_i, \forall i \neq 1$ .
- Let  $f_1$  minimize g(X), and  $f_2$  minimize g(Y)

$$g(X) - g(Y) = \left(\frac{\sum_{i} f_{1}(X_{i})}{n} - Ef_{1}[X_{1}]\right) - \left(\frac{\sum_{i} f_{2}(X_{i})}{n} - Ef_{2}[X_{1}]\right)$$

$$\leq \left(\frac{\sum_{i} f_{1}(X_{i})}{n} - Ef_{1}[X_{1}]\right) - \left(\frac{\sum_{i} f_{1}(X_{i})}{n} - Ef_{1}[X_{1}]\right)$$

$$\leq \frac{2b}{n}$$

#### Concentration

• Using McDiarmid's inequality, we get:

$$P(g(X) - E[g(X)] \ge \epsilon) \le \exp(-\epsilon^2 n/2)$$

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

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

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

### Symmetrization

• Consider an iid copy of X' of X

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

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

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

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

$$= E_{X,X'} \|\hat{P}_{n} - \hat{P}'_{n}\|_{\mathcal{F}}$$

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# Symmetrize again

- Let  $\epsilon_i \in \{1, -1\}$ .
- Note that  $f(X_i) f(X_i')$  is symmetric
- For a symmetric random variable U, and a random variable  $\epsilon \in \{-1,1\}$  (independent of R)

$$P(\epsilon R \le t) = P(R \le t)P(\epsilon = 1) + P(R \ge -t)P(\epsilon = -1)$$
$$= P(R \le t)$$

- Hence  $\sup_{f \in \mathcal{F}} \left| \frac{1}{n} \sum_{i} (f(X_i) f(X_i')) \right|$  and  $\sup_{f \in \mathcal{F}} \left| \frac{1}{n} \sum_{i} \epsilon_i (f(X_i) f(X_i')) \right|$  have the same distribution, and expectation
- We will choose  $\epsilon_i$ 's uniformly, i.e. we will consider Rademacher random variables.

# Rademacher complexity

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

$$= E_{X,X',\epsilon} \sup_{f \in \mathcal{F}} \left| \frac{1}{n} \sum_{i} \epsilon_{i} (f(X_{i}) - f(X'_{i})) \right|$$

$$\leq E_{X,\epsilon} \sup_{f \in \mathcal{F}} \left| \frac{1}{n} \sum_{i} \epsilon_{i} f(X_{i}) \right| + E_{X',\epsilon} \sup_{f \in \mathcal{F}} \left| \frac{1}{n} \sum_{i} \epsilon_{i} f(X'_{i}) \right|$$

$$= 2E \sup_{f \in \mathcal{F}} \left| \frac{1}{n} \sum_{i} \epsilon_{i} f(X_{i}) \right| =: 2\mathcal{R}_{\mathcal{F}}$$

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

## Why the Rademacher complexity?

- We have now shown that  $\|\hat{P}_n P\|_{\mathcal{F}} \le 2\mathcal{R}_{\mathcal{F}} + \epsilon$  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  $\|\hat{P}_n P\|_{\mathcal{F}} \stackrel{a.s.}{\to} 0$ .