CUHK STAT6050: Statistical Learning Theory Spring 2022

Lecture 3: Uniform concentration inequality

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"*There is Nothing More Practical Than A Good Theory.*" — Kurt Lewin

1 Introduction

As indicated in Lecture 2, we will focus on the asymptotics of the empirical process of the estimation error, that is, try to find a $\delta_n \to 0$ for any small $\varepsilon > 0$,

$$\mathbb{P}\big(\sup_{f\in\mathscr{F}} |\widehat{R}_n(f) - R(f)| \geq \varepsilon\big) \leq \delta_n$$

Motivated by **concentration**, how a random variable deviates from its expectation, rewrite the probability as:

$$\mathbb{P}\big(\sup_{f\in\mathscr{F}} |\widehat{R}_n(f) - R(f)| - \mathbb{E}\sup_{f\in\mathscr{F}} |\widehat{R}_n(f) - R(f)| \geq \varepsilon - \mathbb{E}\sup_{f\in\mathscr{F}} |\widehat{R}_n(f) - R(f)|\big) \leq \delta_n.$$

To investigate this bound, we itemize two aims:

- **A1.** The asymptotics of
$$\mathbb{E}\sup_{f\in\mathscr{F}} |\widehat{R}_n(f) - R(f)|.$$
- **A2.** The concentration inequality of
$$\mathbb{P}\big(\sup_{f\in\mathscr{F}} |\widehat{R}_n(f) - R(f)| - \mathbb{E}\sup_{f\in\mathscr{F}} |\widehat{R}_n(f) - R(f)| \geq \varepsilon\big).$$

For **A1**, the minimum requirement is that

$$\mathbb{E}\sup_{f\in\mathscr{F}} |\widehat{R}_n(f) - R(f)| = o_P(1),$$

to ensure asymptotically vanishing of (the upper bound of) the estimation error. For **A2**, we can regard it as a uniform version of concentration inequalities.

2 From pointwise to uniform

2.1 From Hoeffding's inequality to McDiarmid's inequality

Theorem 2.1 (Hoeffding's Inequality)**.** *Suppose $Z_1, \cdots, Z_n$ are independent random variables such that $a_i \leq Z_i \leq b_i$ almost surely, then for any $\varepsilon > 0$:*

$$\mathbb{P}\big(\frac{1}{n}\sum_{i=1}^{n} Z_i - \frac{1}{n}\sum_{i=1}^{n}\mathbb{E}(Z_i) \geq \varepsilon\big) \leq \exp\big(\frac{-2n^2\varepsilon^2}{\sum_{i=1}^{n}(b_i - a_i)^2}\big).$$

Note that we can not use the Hoeffding's inequality of bound **A2**, since there is a supremum on the average. McDiarmid's inequality is a general form of Hoeffding's inequality, which enables we to directly bound the probabilistic bound in **A2**.

Theorem 2.2 (McDiarmid's inequality)**.** *Suppose $Z_1, \cdots, Z_n$ are independent random variables, and there is a function $g : \mathbb{R}^n \to \mathbb{R}$ such that the variation on i-th coordinate is upper bounded, that is, for all $i = 1, \cdots, n$ and all $(z_1, \cdots, z_i, z_i', \cdots z_n)$,*

$$|g(z_1, \cdots, z_i, \cdots, z_n) - g(z_1, \cdots, z_i', \cdots, z_n)| \leq c_i.$$

Then,

$$\mathbb{P}\Big(g(Z_1, \cdots, Z_n) - \mathbb{E}g(Z_1, \cdots, Z_n) \geq \varepsilon\Big) \leq \exp\big(-\frac{2\varepsilon^2}{\sum_{i=1}^{n} c_i}\big).$$

The idea of McDiarmid's inequality is quite similar to Hoeffding's inequality, yet it uses the boundness of the overall function $g(Z_1, \cdots, Z_n)$. We demonstrate the McDiarmid's inequality for our Aim **A2**.

Let $Z_i = l(\mathbf{Y}_i, f(\mathbf{X}_i))$, and

$$g(Z_1, \cdots, Z_n) = \sup_{f \in \mathscr{F}} \big(\widehat{R}_n(f) - R(f)\big) = \sup_{f \in \mathscr{F}} \frac{1}{n}\sum_{i=1}^{n}\big(Z_i - \mathbb{E}l(\mathbf{Y}, f(\mathbf{X}))\big).$$

Assume that $0 \leq l(\mathbf{Y}_i, f(\mathbf{X}_i)) \leq U$, we have

$$|g(z_1, \cdots, z_i, \cdots, z_n) - g(z_1, \cdots, z_i', \cdots, z_n)| \leq \big|\sup_{f \in \mathscr{F}} \frac{1}{n}\big(z_i - z_i'\big)\big| = U/n.$$

Then, McDiarmid's inequality yields that

$$\mathbb{P}\big(\sup_{f \in \mathscr{F}} |\widehat{R}_n(f) - R(f)| - \mathbb{E}\sup_{f \in \mathscr{F}} |\widehat{R}_n(f) - R(f)| \geq \varepsilon\big) \leq \exp\big(-\frac{2n\varepsilon^2}{U^2}\big).$$

We summarize the result as the following corollary.

Corollary 2.3. *For a loss function $l(\cdot, \cdot)$ uniformly bounded by a constant U, then for any $\varepsilon > 0$,*

$$\mathbb{P}\big(\sup_{f \in \mathscr{F}} |\widehat{R}_n(f) - R(f)| - \mathbb{E}\sup_{f \in \mathscr{F}} |\widehat{R}_n(f) - R(f)| \geq \varepsilon\big) \leq \exp\big(-\frac{2n\varepsilon^2}{U^2}\big).$$

Remark 2.4. The information used in Hoeffding's inequality and McDiarmid's inequality: *boundness of the loss function*.

2.2 From Bernstein's inequality to Talagrand's inequality

Hoeffding's inequality does not use any information about the randomness of random variables. Bernstein's inequality is a sharper inequality to consider the *variance of the random variable*.

Theorem 2.5 (Bernstein's inequality)**.** *Let $Z_1, \cdots, Z_n$ be independent random variables with $|Z_i| \leq U$ almost surely, for all $i = 1, \cdots, n$. Then, for all $\varepsilon > 0$,*

$$\mathbb{P}\big(\frac{1}{n}\sum_{i=1}^{n} Z_i - \frac{1}{n}\sum_{i=1}^{n}\mathbb{E}(Z_i) \geq \varepsilon\big) \leq \exp(-\frac{n\varepsilon^2}{2\sigma^2 + 2U\varepsilon/3}),$$

where $\sigma^2 = \frac{1}{n}\sum_{i=1}^{n}\mathbf{Var}(Z_i)$.

The uniform Bernstein's inequality is a much harder problem which was solved by *Talagrand* [Talagrand, 1996b, Talagrand, 1996a].

Theorem 2.6 (Talagrand's inequality)**.** *For a loss function $l(\cdot,\cdot)$ uniformly bounded by a constant U, the for $\varepsilon > 0$,*

$$\mathbb{P}\Big(\sup_{f\in\mathscr{F}} |\widehat{R}_n(f) - R(f)| - \mathbb{E}\sup_{f\in\mathscr{F}} |\widehat{R}_n(f) - R(f)| \geq \varepsilon\Big) \leq K\exp\Big(-\frac{1}{K}\frac{t}{U}\log(1+\frac{tU}{nV})\Big),$$

where $K > 0$ is a universal constant and V is any constant satisfying

$$V \geq \mathbb{E}\sup_{f\in\mathscr{F}}\frac{1}{n}\sum_{i=1}^{n}\Big(l\big(\mathbf{Y}_i, f(\mathbf{X}_i)\big) - \mathbb{E}l\big(\mathbf{Y}_i, f(\mathbf{X}_i)\big)\Big)^2.$$

The constant V is analog to the variance in Bernstein's inequality. However, find a tight constant V to bound the "variance" of the functional space is not easy. Now, given the results of Talagrand's inequality, we slight modify our aims:

- **A1.** The asymptotics of
$$\mathbb{E}\sup_{f\in\mathscr{F}} |\widehat{R}_n(f) - R(f)|.$$
- **A2′.** Find a tight constant V such that
$$V \geq \mathbb{E}\sup_{f\in\mathscr{F}}\frac{1}{n}\sum_{i=1}^{n}\Big(l\big(\mathbf{Y}_i, f(\mathbf{X}_i)\big) - \mathbb{E}l\big(\mathbf{Y}_i, f(\mathbf{X}_i)\big)\Big)^2.$$

In the sequel, we will show that **A1** and **A2′** are crossed in the same direction.

References

[Talagrand, 1996a] Talagrand, M. (1996a). New concentration inequalities in product spaces. *Inventiones mathematicae*, 126(3):505–563.

[Talagrand, 1996b] Talagrand, M. (1996b). A new look at independence. *The Annals of probability*, pages 1–34.