

Chapter 20

Sample Error (Variance)

Recall that the sample error is bounded by

$$\mathcal{S}(\hat{h}_N) := \mathcal{R}(\hat{h}_N) - \mathcal{R}(\hat{h}) \leq |\mathcal{R}(\hat{h}_N) - \mathcal{R}_N(\hat{h}_N)| + |\mathcal{R}_N(\hat{h}) - \mathcal{R}(\hat{h})|. \quad (20.1)$$

The two terms on the right hand side of (20.1) are the sampling errors for $\mathcal{R}(\hat{h}_N)$ and $\mathcal{R}(\hat{h})$ using Monte Carlo. Chapter ?? tells us that these errors for finite sample size¹ N can be bounded probabilistically.

20.1 Sampling error for a function in \mathcal{H}

Lemma 20.1. *Assume that \mathcal{H} is M -bounded in the sense of Assumption 17.1. For any $h \in \mathcal{H}$, there holds*

$$\mathbb{P}[|\mathcal{R}_N(h) - \mathcal{R}(h)| > t] \leq 2e^{-2N \frac{t^2}{M^4}}, \quad \forall t \geq 0.$$

Proof. The proof is obvious using the M -boundedness of \mathcal{H} , the i.i.d. assumption 16.1 on the training set S , and the result of Exercise 14.3. \square

20.2 Sampling error for finite \mathcal{H}

We now extend Section 20.1 to hypothesis space \mathcal{H} containing finite number of functions h_1, \dots, h_N . The task at hand is to probabilistically bound the worst error among h_1, \dots, h_N .

Lemma 20.2. *Let $\mathcal{H} = \{h_1, \dots, h_N\}$, \mathcal{H} is M -bounded, and the training set S is i.i.d. in the sense of Assumption 16.1. There holds:*

¹ Again, this is the beauty of concentration of measures for non-asymptotic theory.

$$\mathbb{P}[|\mathcal{R}_N(h) - \mathcal{R}(h)| > \varepsilon] \leq 2\mathcal{N} e^{-2N \frac{\varepsilon^2}{M^4}}, \quad \forall \varepsilon \geq 0.$$

Proof. We start with the following observation

$$\sup_{h \in \mathcal{H}} |\mathcal{R}_N(h) - \mathcal{R}(h)| > \varepsilon \iff \exists i \leq m : |\mathcal{R}_N(h_i) - \mathcal{R}(h_i)| > \varepsilon,$$

and hence the following identity of on the equivalent events

$$\begin{aligned} \left\{ \sup_{h \in \mathcal{H}} |\mathcal{R}_N(h) - \mathcal{R}(h)| > \varepsilon \right\} &= \{ \exists i \leq m : |\mathcal{R}_N(h_i) - \mathcal{R}(h_i)| > \varepsilon \} \\ &= \cup_{i=1}^{\mathcal{N}} \{ |\mathcal{R}_N(h_i) - \mathcal{R}(h_i)| > \varepsilon \}. \end{aligned}$$

This leads to

$$\begin{aligned} \mathbb{P} \left[\sup_{h \in \mathcal{H}} |\mathcal{R}_N(h) - \mathcal{R}(h)| > \varepsilon \right] &= \mathbb{P}[\exists i \leq m : |\mathcal{R}_N(h_i) - \mathcal{R}(h_i)| > \varepsilon] \\ &= \mathbb{P} \left[\cup_{i=1}^{\mathcal{N}} \{ |\mathcal{R}_N(h_i) - \mathcal{R}(h_i)| > \varepsilon \} \right] \leq \sum_{i=1}^{\mathcal{N}} \mathbb{P}[|\mathcal{R}_N(h_i) - \mathcal{R}(h_i)| > \varepsilon] \leq 2\mathcal{N} e^{-2N \frac{\varepsilon^2}{M^4}}, \end{aligned}$$

where we have used the union bound in Lemma 12.3 in the second last inequality, and the i.i.d. nature of S together with Lemma 20.1 in the last inequality. \square

20.3 Sampling error when \mathcal{H} is a ball with radius R

Let $\mathcal{H} := \{h \in \mathbb{C}(X) : \|h\|_\infty \leq R\}$. Due to the continuity of the sampling error in Exercise 17.2, i.e.,

$$|\mathcal{E}(h_1) - \mathcal{E}(h_2)| \leq 4M \|h_1 - h_2\|_\infty, \quad \forall h_1, h_2 \in \mathcal{H},$$

we have

$$\mathcal{E}(h_c) \geq \mathcal{E}(h) - 4MR,$$

where h_c is the center of the ball and h is an arbitrary function inside the ball. Thus

$$\mathcal{E}(h_c) \geq \sup_{h \in \mathcal{H}} \mathcal{E}(h) - 4MR,$$

which, in turn, shows that if the following implication holds true:

$$\sup_{h \in \mathcal{H}} |\mathcal{E}(h)| \geq \varepsilon \Rightarrow |\mathcal{E}(h_c)| \geq \varepsilon - 4MR.$$

We conclude that

$$\mathbb{P} \left[\left\{ \sup_{h \in \mathcal{H}} |\mathcal{E}(h)| \geq \varepsilon \right\} \right] \leq \mathbb{P} [\{ |\mathcal{E}(h_c)| \geq \varepsilon - 4MR \}] \leq 2e^{-2N \frac{(\varepsilon - 4MR)^2}{M^4}},$$

where we have used Lemma 20.1 in the last inequality. We thus have proved the following result.

Lemma 20.3. *Assume $\mathcal{H} := \{h \in \mathbb{C}(X) : \|h\|_\infty \leq R\}$, and \mathcal{H} is M -bounded in the sense of Assumption 17.1. Then the tail of the worst sampling error decays exponentially, i.e.,*

$$\mathbb{P} \left[\left\{ \sup_{h \in \mathcal{H}} |\mathcal{E}(h)| \geq \varepsilon \right\} \right] \leq 2e^{-2N \frac{(\varepsilon - 4MR)^2}{M^4}}.$$

20.4 Sampling error when \mathcal{H} is a union of \mathcal{N} balls

Without loss of generality we assume that all the balls have the same radius of $\varepsilon/8M$, i.e., $\mathcal{H} = \cup_{i=1}^{\mathcal{N}} B_{h_i} \left(\frac{\varepsilon}{8M} \right)$.

Lemma 20.4. *Assume \mathcal{H} is M -bounded in the sense of Assumption 17.1. Then the tail of the worst sampling error decays exponentially, i.e.,*

$$\mathbb{P} \left[\left\{ \sup_{h \in \mathcal{H}} |\mathcal{E}(h)| \geq \varepsilon \right\} \right] \leq 2\mathcal{N} e^{-N \frac{\varepsilon^2}{2M^4}}.$$

Proof. We proceed with the following observation

$$\sup_{h \in \mathcal{H}} |\mathcal{E}(h)| \geq \varepsilon \iff \exists i \leq \mathcal{N} : \sup_{h \in B_{h_i} \left(\frac{\varepsilon}{8M} \right)} |\mathcal{E}(h)| \geq \varepsilon,$$

which, by the union bound in Lemma 12.3, implies

$$\mathbb{P} \left[\left\{ \sup_{h \in \mathcal{H}} |\mathcal{E}(h)| \geq \varepsilon \right\} \right] \leq \sum_{i=1}^{\mathcal{N}} \mathbb{P} \left[\left\{ \sup_{h \in B_{h_i} \left(\frac{\varepsilon}{8M} \right)} |\mathcal{E}(h)| \geq \varepsilon \right\} \right],$$

which ends the proof by invoking Lemma 20.3. \square

20.5 Sample error for finite dimensional \mathcal{H}

Let $W := \text{span}(\phi_1, \dots, \phi_n) \subset \mathbb{C}(X)$ and the hypothesis space \mathcal{H} be given as

$$\mathcal{H} := \{h \in W : \|h\|_\infty \leq R\}.$$

Lemma 20.5. *Assume \mathcal{H} is M -bounded in the sense of Assumption 17.1. Then the tail of the worst sampling error decays exponentially, i.e.,*

$$\mathbb{P} \left[\left\{ \sup_{h \in \mathcal{H}} |\mathcal{E}(h)| \geq \varepsilon \right\} \right] \leq 2\mathcal{N} \left(\mathcal{H}, \frac{\varepsilon}{8M} \right) e^{-N \frac{\varepsilon^2}{2M^4}},$$

where

$$\mathcal{N} \left(\mathcal{H}, \frac{\varepsilon}{8M} \right) \leq \left(\frac{16RM}{\varepsilon} + 1 \right)^n.$$

Proof. The bound of the covering number of \mathcal{H} using balls with radii $\varepsilon/8M$, $\mathcal{N} \left(\mathcal{H}, \frac{\varepsilon}{8M} \right)$, is provided in Proposition 20.1. The assertion is readily available using Lemma 20.4. \square

20.6 Sampling error when \mathcal{H} is compact

In this section we assume that \mathcal{H} is a compact subset of $\mathbb{C}(X)$. From Lemma 20.2 we know that the covering number $\mathcal{N} \left(\mathcal{H}, \frac{\varepsilon}{8M} \right)$ for \mathcal{H} is finite.² The sample error in Lemma 20.5 is still valid, but in this case we leave the covering number $\mathcal{N} \left(\mathcal{H}, \frac{\varepsilon}{8M} \right)$ undefined/unestimated.

20.7 Sample error

We are now in the position to estimate the sample error $\mathcal{S}(\hat{h}_N)$ by bounding the two sampling errors on the right hand side of (20.1). To be concrete we consider the case when \mathcal{H} is a compact subset of $\mathbb{C}(X)$, and this in fact covers the other cases except³ the case in Section 20.3.

Since \hat{h} is a deterministic function, we can use the sampling error estimation in Section 20.1 to conclude that

$$|\mathcal{R}_N(\hat{h}) - \mathcal{R}(\hat{h})| \leq \frac{\varepsilon}{2}$$

with the probability at least

$$1 - 2e^{-N \frac{\varepsilon^2}{2M^4}}.$$

Now, as remarked in Section 16.2, \hat{h}_N is a random function and we have to employ the worst case error to bound $|\mathcal{R}(\hat{h}_N) - \mathcal{R}_N(\hat{h}_N)|$. Lemma 20.5 says that

$$|\mathcal{R}(\hat{h}_N) - \mathcal{R}_N(\hat{h}_N)| \leq \frac{\varepsilon}{2}$$

Nothing less will do!

² The subject of estimating covering numbers is standard (but technical) in functional analysis, we refer the readers to [13].

³ The reason is that balls in infinite dimensional spaces are not compact!

with the probability at least

$$1 - 2\mathcal{N}\left(\mathcal{H}, \frac{\varepsilon}{16M}\right) e^{-N \frac{\varepsilon^2}{8M^4}}.$$

Combining these results we conclude that the sample error is bounded by any ε , i.e.,

$$\mathcal{S}(\hat{h}_N) \leq \varepsilon$$

with the probability at least

$$\begin{aligned} \left[1 - 2e^{-N \frac{\varepsilon^2}{2M^4}}\right] \times \left[1 - 2\mathcal{N}\left(\mathcal{H}, \frac{\varepsilon}{16M}\right) e^{-N \frac{\varepsilon^2}{8M^4}}\right] \\ \geq 1 - 2\left[\mathcal{N}\left(\mathcal{H}, \frac{\varepsilon}{16M}\right) + 1\right] e^{-N \frac{\varepsilon^2}{8M^4}}. \end{aligned}$$

In summary we have proved the following result.

Theorem 20.1 (Sample error estimation). *Suppose \mathcal{H} is a compact subset of $\mathbb{C}(X)$ and \mathcal{H} is M -bounded. The following estimation of the sample error*

$$\mathcal{S}(\hat{h}_N) \leq \varepsilon, \quad \varepsilon > 0,$$

holds true with probability at least

$$1 - 2\left[\mathcal{N}\left(\mathcal{H}, \frac{\varepsilon}{16M}\right) + 1\right] e^{-N \frac{\varepsilon^2}{8M^4}}.$$

20.8 Appendix

Definition 20.1 (ε -net). Let \mathcal{H} be a metric space with a metric $\|\cdot\|$. A subset W of \mathcal{H} is called a ε -net of \mathcal{H} if any point in \mathcal{H} is within ε -distance from a point in W , i.e.,

$$\forall h \in \mathcal{H}, \exists h_0 \in W : \|h - h_0\| \leq \varepsilon.$$

Equivalently, a subset W of \mathcal{H} is called a ε -net of \mathcal{H} if and only if \mathcal{H} can be covered by balls of radius ε with centers in W .

Definition 20.2 (Covering number). Let \mathcal{H} be a metric space and $\eta > 0$. The covering number $\mathcal{N}(\mathcal{H}, \eta)$ is defined as the minimal number such that there exist $\mathcal{N}(\mathcal{H}, \eta)$ balls in \mathcal{H} with radius η covering \mathcal{H} .

Proposition 20.1 (Covering number for a ball in finite dimensional space). *Let n be the dimension of a Banach space W and $\mathcal{H} := \{h \in W : \|h\|_\infty \leq R\} = B_0(R)$. Then for $0 < \eta < R$, we have*

$$\mathcal{N}(\mathcal{H}, \eta) \leq \left(\frac{2R}{\eta} + 1\right)^n.$$

Since $\mathcal{N}(B_0(R), \eta) = \mathcal{N}(B_0(1), \eta/R)$, it is sufficient to consider unit ball in W .

Proposition 20.2 (Finite cover of compact sets). *Let \mathcal{H} be a compact subset of $\mathbb{C}(X)$, then there exists a finite cover for \mathcal{H} .*