Theoretical Deep Learning

Lecture 3: Uniform bounds and empirical processes

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1 Uniform bounds of generalization gap

Let $\mathcal{H}$ be the hypothesis class. Consider the estimator:

$$\hat{h}_n = \operatorname*{argmin}_{h \in \mathcal{H}} \hat{\mathcal{R}}_n(h).$$

This estimator guarantees the smallness of the empirical risk. But the question is: How small is the true error $\mathcal{R}(\hat{h}_n)$? This is equivalent to control the generalization gap:

$$\mathcal{R}(\hat{h}_n) - \hat{\mathcal{R}}_n(\hat{h}_n). \tag{1.1}$$

Unfortunately, concentration inequalities cannot be applied directly since $\hat{h}_n$ depends on the training set. To deal with this dependence, we can consider the uniform bound

$$|\mathcal{R}(\hat{h}_n) - \hat{\mathcal{R}}_n(\hat{h}_n)| \leq \sup_{h \in \mathcal{H}} |\mathcal{R}(h) - \hat{\mathcal{R}}_n(h)|. \tag{1.2}$$

Obviously, when the hypothesis space $\mathcal{H}$ is sufficiently "small", e.g., the extreme case: $\mathcal{H} = \{h\}$, it is expected that

$$\sup_{h \in \mathcal{H}} |\mathcal{R}(h) - \hat{\mathcal{R}}_n(h)| \sim \frac{1}{\sqrt{n}}.$$

Some natural questions go as follows.

- What kind of $\mathcal{H}$ can guarantee the smallness of uniform bound?
- What is the rate? Do we still have $O(1/\sqrt{n})$?

Let us first look at a simple example: finite hypothesis class.

Lemma 1.1. *Assume $|\mathcal{H}| < \infty$ and $\sup_{y,y'} |\ell(y, y')| \leq 1$. For any $\delta \in (0, 1)$, with probability $1 - \delta$ over the random sampling of training set S, we have*

$$\sup_{h \in \mathcal{H}} |\mathcal{R}(h) - \hat{\mathcal{R}}_n(h)| \leq \sqrt{\frac{2 \ln(2|\mathcal{H}|/\delta)}{n}}.$$

Proof. Let $Z(h, X) = \ell(h(X), h^*(X))$. Taking the union bound gives us

$$\mathbb{P}\left\{\sup_{h \in \mathcal{H}} |\frac{1}{n}\sum_{i=1}^n Z(h, X_i) - \mathbb{E}[Z(h, X)]| \geq t\right\} \leq \sum_{j=1}^m \mathbb{P}\left\{\left|\frac{1}{n}\sum_{i=1}^n Z(h_j, X_i) - \mathbb{E}[Z(h_j, X)]\right| \geq t\right\} \tag{1.3}$$

$$\leq m 2 e^{\frac{-2nt^2}{2^2}} = 2m e^{\frac{-nt^2}{2}}. \tag{1.4}$$

Let the failure probability $2me^{\frac{-nt^2}{2}} = \delta$, which leads to $t = \sqrt{\frac{2\ln(2m/\delta)}{n}}$.

□

The upper bound only depends on $|\mathcal{H}|$ logarithmically. Hence, even when the hypothesis class has exponentially many functions, the generalization gap can be still well controlled.

Definition 1.2 (Empirical process)**.** Let $\mathcal{F}$ be a class of real-valued functions $f : \Omega \mapsto \mathbb{R}$ where (Ω, Σ, μ) is a probability space. Let $X \sim \mu$ and $X_1, \ldots, X_n$ be independent copies of X. Then, the random process $(X_f)_{f \in \mathcal{F}}$ defined by

$$X_f := \frac{1}{n} \sum_{i=1}^{n} f(X_i) - \mathbb{E}\, f(X)$$

is called an *empirical process* indexed by $\mathcal{F}$.

In our case, $f(X) = \ell(h(X), h^*(X))$. Our task is to bound the suprema:

$$\sup_{f \in \mathcal{F}} |X_f|.$$

Note that the above quantity can viewed a "weak" distance between μ and the empirical measure $\hat{\mu}_n = \frac{1}{n} \sum_{i=1}^{n} \delta(\cdot - x_i)$ with the test functions given by $\mathcal{F}$:

$$d_{\mathcal{F}}(\hat{\mu}_n, \mu) := \sup_{f \in \mathcal{F}} |\, \mathbb{E}_{\hat{\mu}_n} f - \mathbb{E}_{\mu} f|.$$

2 Rademacher complexity

Lemma 2.1 (Symmetrization of empirical processes)**.**

$$\mathbb{E} \sup_{f \in \mathcal{F}} \left[\frac{1}{n} \sum_{i=1}^{n} f(X_i) - \mathbb{E}\, f(X) \right] \leq 2\, \mathbb{E} \sup_{f \in \mathcal{F}} [\frac{1}{n} \sum_{i=1}^{n} \xi_i f(X_i)],$$

where $\xi_1, \ldots, \xi_n$ are i.i.d. Rademacher random variable: $\mathbb{P}(\xi = 1) = \mathbb{P}(\xi = -1) = \frac{1}{2}$

Proof. Let X_i' be an independent copy of X_i. To simplify the notation, we use $\mathbb{E}_{X_i}$ and $\mathbb{E}_{X_i'}$ to denote the expectation with respect to $\{X_i\}_{i=1}^n$ and $\{X_i'\}_{i=1}^n$, respectively. Then,

$$\begin{aligned}
\mathbb{E} \sup_{f \in \mathcal{F}} [\frac{1}{n} \sum_{i=1}^{n} f(X_i) - \mathbb{E}\, f(X)] &= \mathbb{E}_{X_i} \sup_{f \in \mathcal{F}} \mathbb{E}_{X_i'} [\frac{1}{n} \sum_{i=1}^{n} (f(X_i) - f(X_i'))] && (2.1) \\
&\leq \mathbb{E}_{X_i, X_i'} \sup_{f \in \mathcal{F}} [\frac{1}{n} \sum_{i=1}^{n} (f(X_i) - f(X_i'))] && (2.2)
\end{aligned}$$

Due to that $f(X_i) - f(X_i')$ is symmetric, for any $\{\xi_i\} \in \{\pm 1\}^n$, we have

$$\begin{aligned}
\mathbb{E}_{X_i, X_i'} \sup_{f \in \mathcal{F}} [\frac{1}{n} \sum_{i=1}^{n} f(X_i) - f(X_i')] &= \mathbb{E}_{X_i, X_i'} \sup_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^{n} \xi_i [f(X_i) - f(X_i')] \\
&= \mathbb{E}_{X_i, X_i', \xi} \sup_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^{n} \xi_i [f(X_i) - f(X_i')] \\
&\leq \mathbb{E}_{X_i, X_i', \xi} [\sup_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^{n} \xi_i f(X_i) - \inf_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^{n} \xi_i f(X_i')]
\end{aligned}$$

$$= 2\,\mathbb{E}_{X_i,\xi} \sup_{f\in\mathcal{F}} \frac{1}{n}\sum_{i=1}^n \xi_i f(X_i)$$

$\square$

Definition 2.2 (Rademacher complexity)**.** The empirical Rademacher complexity of a function class $\mathcal{F}$ on finite samples is defined as

$$\widehat{\mathrm{Rad}}_n(\mathcal{F}) = \mathbb{E}_\xi[\sup_{f\in\mathcal{F}} \frac{1}{n}\sum_{i=1}^n \xi_i f(X_i)].$$

The population Rademacher complexity is given by

$$\mathrm{Rad}_n(\mathcal{F}) = \mathbb{E}_S[\widehat{\mathrm{Rad}}_n(\mathcal{F})].$$

The symmetrization lemma 2.1 implies that

$$\mathbb{E}\sup_{f\in\mathcal{F}} \left[\frac{1}{n}\sum_{i=1}^n f(X_i) - \mathbb{E}\, f(X)\right] \le 2\,\mathrm{Rad}_n(\mathcal{F}). \tag{2.3}$$

Theorem 2.3. *Assume that $0 \le f \le B$ for all $f \in \mathcal{F}$. For any $\delta \in (0,1)$, with probability at least $1-\delta$ over the choice of the training set $S = \{X_1,\dots,X_n\}$, we have*

$$\sup_{f\in\mathcal{F}} \left|\frac{1}{n}\sum_{i=1}^n f\left(X_i\right) - \mathbb{E}f(X)\right| \le 2\,\mathrm{Rad}_n(\mathcal{F}) + B\sqrt{\frac{\log(2/\delta)}{2n}},$$

and the sample-dependent version:

$$\sup_{f\in\mathcal{F}} \left|\frac{1}{n}\sum_{i=1}^n f\left(X_i\right) - \mathbb{E}f(X)\right| \le 2\widehat{\mathrm{Rad}}_n(\mathcal{F}) + 3B\sqrt{\frac{\log(4/\delta)}{n}}.$$

Proof. Let

$$g\left(x_1,\dots,x_n\right) = \sup_{f\in\mathcal{F}} \left[\frac{1}{n}\sum_{i=1}^n f\left(x_i\right) - \mathbb{E}f(X)\right]$$

and note that

$$\sup_\alpha g\left(x_1,\dots,x_{i-1},\alpha,x_{i+1},\dots,x_n\right) - \inf_\alpha g\left(x_1,\dots,x_{i-1},\alpha,x_{i+1},\dots,x_n\right) \le \frac{B}{n}.$$

By McDiarmid's inequality,

$$\mathbb{P}\{|g(X_1,\dots,X_n) - \mathbb{E}\,g| \ge t\} \le 2e^{-\frac{2nt^2}{B^2}}.$$

Let the failure probability $2e^{-\frac{2nt^2}{B^2}} = \delta$, which leads to $t = \sqrt{\frac{2B\log(2/\delta)}{n}}$. This proves the first statement. Analogously, using again the McDiarmid's inequality to $g'\left(x_1,\dots,x_n\right) = \mathbb{E}_\xi \sup_{f\in\mathcal{F}}\left[\frac{1}{n}\sum_{i=1}^n \xi_i f\left(x_i\right)\right]$ leads to the sample-dependent one. $\square$

- Let $\mathcal{F} = \{f\}$. Then,

$$\widehat{\mathrm{Rad}}_n(\mathcal{F}) = \mathbb{E}_\xi[\frac{1}{n}\sum_{i=1}^n \xi_i f(x_i)] = 0.$$

- Two functions. Let $\mathcal{F} = \{f_{-1}, f_1\}$ where $f_{-1} \equiv -1$ and $f_1 \equiv 1$.

$$\sqrt{n}\widehat{\mathrm{Rad}}_n(\mathcal{F}) = \mathbb{E}_\xi \sup_{f \in \{-1,+1\}} f \frac{1}{\sqrt{n}} \sum_{i=1}^n \xi = \mathbb{E}_\xi \, |\frac{1}{\sqrt{n}} \sum_{i=1}^n \xi_i| \to \mathbb{E}_{Z\sim\mathcal{N}(0,1)} |Z| = \sqrt{\frac{2}{\pi}}.$$

  Hence, when n is sufficiently large,

$$\mathrm{Rad}_n(\mathcal{F}) \sim \sqrt{\frac{2}{n\pi}}.$$

Lemma 2.4 (Massart's lemma)**.** *Assume that* $\sup_{x\in\mathcal{X}, f\in\mathcal{F}} |f| \le B$ *and* $\mathcal{F}$ *is finite. Then,*

$$\widehat{\mathrm{Rad}}_n(\mathcal{F}) \le B\sqrt{\frac{2\log|\mathcal{F}|}{n}}.$$

Proof. Let $Z_f = \sum_{i=1}^n \xi_i f(x_i)$. Then,

$$\mathbb{E}[e^{\lambda Z_f}] = \prod_{i=1}^n \mathbb{E}[e^{\lambda \xi_i f(x_i)}] \le \prod_{i=1}^n e^{\lambda^2 \frac{(B-(-B))^2}{8}} = e^{\frac{\lambda^2 n B^2}{2}}.$$

Hence, Z_f is sub-Gaussian with the variance proxy $\sigma^2 = \sqrt{n}B$. Using the maximal inequality, we have

$$\widehat{\mathrm{Rad}}_n(\mathcal{F}) = \frac{1}{n}\,\mathbb{E}_\xi[\sup_{f\in\mathcal{F}} Z_f] \le \frac{1}{n}\cdot\sqrt{n}B\sqrt{2\log|\mathcal{F}|} = B\sqrt{\frac{2\log|\mathcal{F}|}{n}}. \tag{2.4}$$

□

Applying Massart's lemma to bound the generalization gap recovers Lemma 1.1.

Linear functions. Let $\mathcal{F} = \{w^T x : \|w\|_p \le 1\}$. Let q be the conjugate of p, i.e., $1/q + 1/p = 1$. Then,

$$\widehat{\mathrm{Rad}}_n(\mathcal{F}) = \mathbb{E}_\xi \sup_{\|w\|_p\le 1} \frac{1}{n}\sum_{i=1}^n \xi_i w^T X_i = \mathbb{E}_\xi \sup_{\|w\|_p \le 1} w^T\left(\frac{1}{n}\sum_{i=1}^n \xi_i X_i\right) = \mathbb{E}_\xi \, \|\frac{1}{n}\sum_{i=1}^n \xi_i X_i\|_q. \tag{2.5}$$

Lemma 2.5. *Assume that* $\|x_i\|_q \le 1$ *for all* $x_i \in S$*. Then,*

- *If* $p = 2$*, then*

$$\widehat{\mathrm{Rad}}_n(\mathcal{F}) \le \sqrt{\frac{1}{n}}.$$

- *If* $p = 1$*, then,*

$$\widehat{\mathrm{Rad}}_n(\mathcal{F}) \le \sqrt{\frac{2\log(2d)}{n}}.$$

Proof. For the case where $p = 2$,

$$\widehat{\mathrm{Rad}}_n(\mathcal{F}) \le \mathbb{E}_\xi \, \| \frac{1}{n} \sum_{i=1}^n \xi_i x_i \|_2 \le \sqrt{\mathbb{E}_\xi \, \| \frac{1}{n} \sum_{i=1}^n \xi_i x_i \|_2^2}$$
$$= \sqrt{\frac{1}{n^2} \sum_{i,j=1}^n x_i x_j \, \mathbb{E}[\xi_i \xi_j]} = \sqrt{\frac{1}{n} \sum_{i=1}^n x_i^2} \le \sqrt{\frac{1}{n}}.$$

The case of $p = 1$ leaves to homework. □

We have shown the Rademacher complexity of linear functions. To obtain the estimates of more general classes, we need follow results.

Lemma 2.6 (Rademacher calculus)**.** *The Rademacher complexity has the following properties.*

- $\mathrm{Rad}_n(\lambda \mathcal{F}) = |\lambda| \, \mathrm{Rad}_n(\mathcal{F})$.
- $\mathrm{Rad}_n(\mathcal{F} + f_0) = \mathrm{Rad}_n(\mathcal{F})$.
- *Let Conv*$(\mathcal{F})$ *denote the convex hull of* $\mathcal{F}$ *defined by*

$$\textit{Conv}(\mathcal{F}) = \Big\{ \sum_{j=1}^m a_j f_j : \alpha_j \ge 0, \sum_{j=1}^m a_j = 1, f_1, \ldots, f_m \in \mathcal{F}, m \in \mathbb{N}_+ \Big\}.$$

  Then, we have $\mathrm{Rad}_n(\textit{Conv}(\mathcal{F})) = \mathrm{Rad}_n(\mathcal{F})$.

Proof. Here, we only prove the third result. By definition,

$$\begin{aligned} n\widehat{\mathrm{Rad}}_n(\mathrm{Conv}(\mathcal{F})) &= \mathbb{E} \sup_{f_j \in \mathcal{F}, \|\alpha\|_1 = 1} \sum_{i=1}^n \xi_i \sum_{j=1}^m a_j f_j(X_i) \\ &= \mathbb{E} \sup_{f_j \in \mathcal{F}, \|\alpha\|_1 = 1} \sum_{j=1}^m a_j \sum_{i=1}^n \xi_i f_j(X_i) \\ &= \mathbb{E} \sup_{f_j \in \mathcal{F}} \max_j \sum_{i=1}^n \xi_i f_j(X_i) \\ &= \mathbb{E} \sup_{f \in \mathcal{F}} \sum_{i=1}^n \xi_i f(X_i) = n\widehat{\mathrm{Rad}}_n(\mathcal{F}) \end{aligned}$$

□

Lemma 2.7 (Ledoux & Talagrand 2011, Contraction lemma)**.** *Let* $\varphi_i : \mathbb{R} \mapsto \mathbb{R}$ *with* $i = 1, \ldots, n$ *be* β*-Lispchitz continuous. Then,*

$$\frac{1}{n} \mathbb{E}_\xi \sup_{f \in \mathcal{F}} \sum_{i=1}^n \xi_i \varphi_i \circ f(x_i) \le \mu \, \widehat{\mathrm{Rad}}_n(\mathcal{F}).$$

Proof. WLOG, assume $\beta = 1$. Let $\hat{\xi} = (\xi_1, \ldots, \xi_n)$ and $Z_k(f) = \sum_{i=1}^k \xi_i \varphi_i \circ f(x_i)$. Then,

$$\begin{aligned}
\mathbb{E}_{\xi_n} \sup_{f\in\mathcal{F}} \sum_{i=1}^n \xi_i \varphi_i \circ f(x_i) &= \frac{1}{2}\left[\sup_{f\in\mathcal{F}}(Z_{n-1}(f) + \varphi_n \circ f(x_n)) + \sup_{f\in\mathcal{F}}(Z_{n-1}(f) - \varphi_n \circ f(x_n))\right] \\
&= \frac{1}{2} \sup_{f,f'\in\mathcal{F}} \Big(Z_{n-1}(f) + Z_{n-1}(f') + \varphi_n \circ f(x_n) - \varphi_n \circ f'(x_n)\Big) \\
&\le \frac{1}{2} \sup_{f,f'\in\mathcal{F}} \Big(Z_{n-1}(f) + Z_{n-1}(f') + |f(x_n) - f'(x_n)|\Big) \\
&\le \frac{1}{2} \sup_{f,f'\in\mathcal{F}} \Big(Z_{n-1}(f) + Z_{n-1}(f') + (f(x_n) - f'(x_n))\Big) \quad \text{(Use the symmetry)} \\
&= \frac{1}{2}\left[\sup_{f\in\mathcal{F}}(Z_{n-1}(f) + f(x_n)) + \sup_{f\in\mathcal{F}}(Z_{n-1}(f) - f(x_n))\right] \\
&= \mathbb{E}_{\xi_n} \sup_{f\in\mathcal{F}}(Z_{n-1}(f) + \xi_n f(x_n)).
\end{aligned}$$

Hence, by induction, we have

$$\begin{aligned}
\mathbb{E}_{\hat{\xi}}[\sup_{f\in\mathcal{F}} Z_n(f)] &\le \mathbb{E}_{\hat{\xi}} \sup_{f\in\mathcal{F}}(Z_{n-1}(f) + \xi_n f(x_n)) \\
&\le \mathbb{E}_{\hat{\xi}} \sup_{f\in\mathcal{F}}(Z_{n-2}(f) + \xi_{n-1} f(x_{n-1}) + \xi_n f(x_n)) \\
&\le \mathbb{E}_{\hat{\xi}} \sup_{f\in\mathcal{F}}(\xi_1 f(x_1) + \cdots + \xi_n f(x_n)) \\
&= n\widehat{\mathrm{Rad}}_n(\mathcal{F}). \qquad (2.6)
\end{aligned}$$

□

3 Metric entropy

For the finite hypothesis classes, we have shown that $\log|\mathcal{F}|$, i.e., the logarithm of cardinality, can be used as a good complexity measure. Can we extend this observation to the case where $|\mathcal{F}| = \infty$. One possible approach is *discretization*. This means that we choose a finite subset $\mathcal{F}_\varepsilon \subset \mathcal{F}$ to "represent" $\mathcal{F}$.

Definition 3.1. Consider a metric space (T, ρ).

- We say $T_\varepsilon \subset T$ is a ε-cover of T, if for any $t \in T$, there exists a $t' \in T_\varepsilon$ such that $\rho(t, t') \le \varepsilon$.
- The covering number $\mathcal{N}(\varepsilon, T, \rho)$ is defined as the smallest cardinality of an ε-cover of T with respect to ρ. The *metric entropy* of T is defined by $\log \mathcal{N}(\varepsilon, T, \rho)$.

In the proceeding definition, the metric space (T, ρ) can be arbitrary. However, we focus on the case of $(\mathcal{F}, L^2(\mathbb{P}_n))$, where $\mathcal{F}$ is the hypothesis class and $L^2(\mathbb{P}_n)$ is defined by

$$\|f - f'\|_{L^2(\mathbb{P}_n)} = \sqrt{\frac{1}{n}\sum_{i=1}^n (f(x_i) - f'(x_i))^2}.$$

Here, $(x_1, \dots, x_n)$ denote the finite training samples. Since only the n samples are available, we can really think of these functions as a n-dimensional vector:

$$\hat{f} = (f(x_1), f(x_2), \dots, f(x_n))^T \in \mathbb{R}^n,$$

Obviously, we cannot distinguish functions using information beyond these n-dimensional vectors.

In the following, we show that the Rademacher complexity can be bounded using the metric entropy. To simplify notation, we use $\|\cdot\|$ and $\langle,\rangle$ to denote $L^2(\mathbb{P}_n)$ and the induced inner product. Then,

$$\widehat{\mathrm{Rad}}_n(\mathcal{F}) = \mathbb{E}\sup_{f\in\mathcal{F}}\langle \xi, f\rangle.$$

Proposition 3.2. *Suppose* $\sup_{x\in\mathcal{X}, f\in\mathcal{F}} |f(x)| \le B$. *Then,*

$$\widehat{\mathrm{Rad}}_n(\mathcal{F}) \le \inf_{\varepsilon}\left(\varepsilon + B\sqrt{\frac{2\log\mathcal{N}(\varepsilon, \mathcal{F}, L_2(\mathbb{P}_n))}{n}}\right).$$

Proof. Let $\mathcal{F}_\varepsilon$ be an ε-cover of $\mathcal{F}$ with respect to the metric $L^2(\mathbb{P}_n)$. For any $f \in \mathcal{F}$, let $\pi(f) \in \mathcal{F}_\varepsilon$ such that $\|f - \pi(f)\| \le \varepsilon$. Then,

$$\begin{aligned}
\mathbb{E}\sup_{f\in\mathcal{F}}\langle \xi, f\rangle &= \mathbb{E}\sup_{f\in\mathcal{F}}\Big[\langle \xi, f - \pi(f)\rangle + \langle \xi, \pi(f)\rangle\Big] \\
&\le \mathbb{E}\sup_{f\in\mathcal{F}}\langle \xi, f - \pi(f)\rangle + \mathbb{E}\sup_{f\in\mathcal{F}}\langle \xi, \pi(f)\rangle \\
&\le \mathbb{E}\,\|\xi\|\|f - \pi(f)\| + \mathbb{E}\sup_{f\in\mathcal{F}_\varepsilon}\langle \xi, f\rangle \\
&\le \varepsilon\sqrt{\frac{\mathbb{E}\,\|\xi\|_2^2}{n}} + \widehat{\mathrm{Rad}}_n(\mathcal{F}_\varepsilon) \qquad \text{(Jesson's inequality)} \\
&\le \varepsilon + B\sqrt{\frac{2\log|\mathcal{F}_\varepsilon|}{n}}, \qquad \text{(Massart's lemma).}
\end{aligned}$$

Using the definition of covering number and optimizing over ε, we complete the proof. □

The proceeding lemma provides a result for the one-resolution discretization. In many cases, it may give us sub-optimal bounds of generalization gap. To fix this problem, we need a sophisticated analysis of all the resolutions. This is typically done by using a *chaining* approach introduced by Dudley.

Theorem 3.3 (Dudley's integral inequality)**.** *Assume* $\sup_{f\in\mathcal{F}, x\in\mathcal{X}} \|f - f'\|_{L^2(\mathbb{P}_n)} \le D$.

$$\widehat{\mathrm{Rad}}_n(\mathcal{F}) \le 12\int_0^D \sqrt{\frac{\log\mathcal{N}(\varepsilon, \mathcal{F}, L^2(\mathbb{P}_n))}{n}}\,\mathrm{d}\varepsilon.$$

Figure 1 visualizes the difference between the upper bound given in Proposition 3.2 and the one in Theorem 3.3. Clearly, the latter is smaller.

Proof. Let $D = \sup_{f,f'\in\mathcal{F}}\|f_1 - f_2\|$ be the diameter of $\mathcal{F}$. By the definition, $D \le 2B$. Let $\varepsilon_j = 2^{-j}D$ for $j = 1, \dots, m$ and $\mathcal{F}_j$ be a corresponding ε_j-cover of $\mathcal{F}$. Consider the decomposition

$$f = f - f_m + \sum_{j=1}^{m}(f_j - f_{j-1}), \tag{3.1}$$

where $f_0 = 0$. Notice that

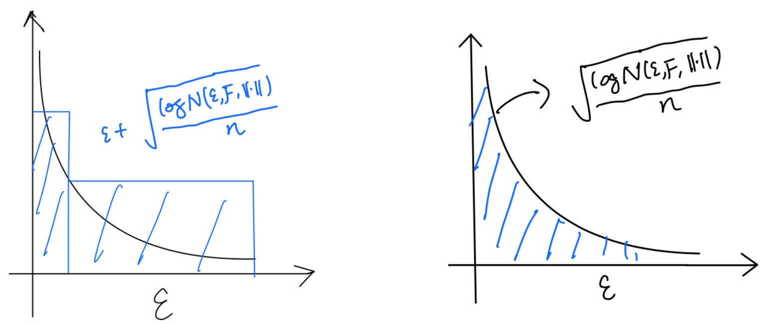

Figure 1: (Left) The result of one-resolution analysis; (Right) The result of chaining.

- $\|f - f_m\| \leq \varepsilon_m$.
- $\|f_j - f_{j-1}\| \leq \|f_j - f\| + \|f - f_{j-1}\| \leq \varepsilon_j + \varepsilon_{j-1} \leq 3\varepsilon_j$.

Then,

$$\begin{aligned}
\widehat{\mathrm{Rad}}_n(\mathcal{F}) &= \mathbb{E} \sup_{f \in \mathcal{F}} \langle \xi, f \rangle \\
&= \mathbb{E} \sup_{f \in \mathcal{F}} \left(\langle \xi, f - g_m \rangle + \sum_{j=1}^{m} \langle \xi, f_j - f_{j-1} \rangle \right) \\
&\leq \varepsilon_m + \mathbb{E} \sup_{f \in \mathcal{F}} \sum_{j=1}^{m} \langle \xi, f_j - f_{j-1} \rangle \\
&\leq \varepsilon_m + \sum_{j=1}^{m} \mathbb{E} \sup_{f \in \mathcal{F}} \langle \xi, f_j - f_{j-1} \rangle \\
&= \varepsilon_m + \sum_{j=1}^{m} \mathbb{E} \sup_{f_j \in \mathcal{F}_j, f_{j-1} \in \mathcal{F}_{j-1}} \langle \xi, f_j - f_{j-1} \rangle \\
&= \varepsilon_m + \sum_{j=1}^{m} \widehat{\mathrm{Rad}}_n(\mathcal{F}_j \cup \mathcal{F}_{j-1}).
\end{aligned}$$

Using the Massart lemma and the fact that $\sup_{f \in \mathcal{F}_j, f' \in \mathcal{F}_{j-1}} \|f_j - f_{j-1}\| \leq 3\varepsilon_j$,

$$\begin{aligned}
\widehat{\mathrm{Rad}}_n(\mathcal{F}) &\leq \varepsilon_m + \sum_{j=1}^{m} 3\varepsilon_j \sqrt{\frac{2\log(|\mathcal{F}_j||\mathcal{F}_{j-1}|)}{n}} \\
&\leq \varepsilon_m + \sum_{j=1}^{m} 6\varepsilon_j \sqrt{\frac{\log |\mathcal{F}_j|}{n}} \\
&= \varepsilon_m + \sum_{j=1}^{m} 12(\varepsilon_j - \varepsilon_{j+1}) \sqrt{\frac{\log \mathcal{N}(\varepsilon_j, \mathcal{F}, L^2(\mathbb{P}_n))}{n}}.
\end{aligned}$$

Taking $m \to \infty$, we obtain

$$\widehat{\mathrm{Rad}}_n(\mathcal{F}) \leq 12 \int_0^D \sqrt{\frac{\log \mathcal{N}(t, \mathcal{F}, L^2(\mathbb{P}_n))}{n}} \, \mathrm{d}t.$$

$\square$

The key ingredient of proceeding analysis is the multi-resolution decomposition (3.1). The technical reason why chaining provides a better estimate is as follows. In the one-resolution discretization, we apply Massart's lemma to functions whose range in $[-1, 1]$, whereas in chaining, we apply Massart's lemma to functions whose range has size $O(\varepsilon_j)$.

Remark 3.4. Metric entropy is actually a more intuitive complexity measure than Rademacher complexity. The essence is discretization and applying Massart's lemma. Moreover, metric entropy is sometimes more convenient to estimate.