

9. VC dimension and Rademacher Complexity

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§6 in [SS] w, Rademacher Complexity taken from §3.1 in Mohri et al.

We've covered ① $|H| < \infty$ (restrictive!)

② HW: axis-aligned rectangles, $|H| = \infty$. $X = \mathbb{R}^d$, $\dim(H) = 2d$

Can we generalize?

We'll cover

① Rademacher Complexity (Mohri, and essentially used in later chapters of [SS])

Simple proofs, but computing R.C. may be impossible (eg, NP-Hard)
especially if ERM_H is difficult to compute

② Growth Function

③ VC-dimension, a way to bound the growth function, and
easier to compute or bound

④ Result: for binary classification, finite VC-dim is

necessary and sufficient for PAC learnability

"Fundamental Thm. of ML"

Rademacher Complexity (§3.1 Mohri, notation adapted a bit)

Will depend on H and loss function

$$\ell : H \times Z \rightarrow \mathbb{R} \text{ in [SS]}$$

$$\lambda : Y \times Y \rightarrow \mathbb{R} \text{ in [Mohri et al.]}$$

$$\text{e.g. } \ell(h, (x, y)) = \lambda(h(x), y)$$

We'll apply to a family of functions

$$F = \{ f : (x, y) \mapsto \ell(h, (x, y)) \mid h \in H \}$$

$$= \lambda \circ H$$

but it'll work for any family of functions F , not just $\lambda \circ H$

$$F \subseteq \mathbb{R}^Z \quad Z = X \times Y$$

Idea

Rademacher Complexity (RC) measures the richness / expressiveness of \mathcal{F} by measuring how well it can fit noise

Def Empirical Rademacher Complexity

\mathcal{F} a family of fcn $f: \mathcal{Z} \rightarrow [a, b]$. Fix $S = (z_1, \dots, z_m)$
then empirical R.C. of \mathcal{F} w.r.t. S is

$$\hat{R}_S(\mathcal{F}) = \mathbb{E}_{\sigma} \left[\sup_{f \in \mathcal{F}} \frac{1}{m} \sum_{i=1}^m \sigma_i \cdot f(z_i) \right]$$

where $\sigma = (\sigma_1, \dots, \sigma_m)$, σ_i iid Rademacher variables

i.e. $\sigma_i = \begin{cases} +1 & \text{w.p. } .5 \\ -1 & \text{w.p. } .5 \end{cases}$ aka symmetric Bernoulli
or uniform on $\{-1, 1\}$

i.e., let $f_S := \begin{bmatrix} f(z_1) \\ \vdots \\ f(z_m) \end{bmatrix} \in \mathbb{R}^m$ then

$$\hat{R}_S(\mathcal{F}) = \frac{1}{m} \mathbb{E}_{\sigma} \underbrace{\sup_{f \in \mathcal{F}} \langle \sigma, f_S \rangle}_{\text{best correlation w/ noise}}$$

Extremes: $\mathcal{F} = \{f\}$, $\hat{R}_S(\{f\}) = \frac{1}{m} \mathbb{E}_{\sigma} \langle \sigma, f_S \rangle = 0$. Best possible

vs. \mathcal{F} = all functions, say $f: \mathcal{Z} \rightarrow \{0, 1\}$, then possible for some S

for $\{f_S : f \in \mathcal{F}\} = \{0, 1\}^m$

Then $\sup_{f \in \mathcal{F}} \langle \sigma, f_S \rangle = m$, so $\hat{R}_S(\mathcal{F}) = \frac{1}{m} \mathbb{E}_{\sigma} m = \underline{\underline{1}}$

worst-possible
(if $[a, b] = [0, 1]$)

Def Rademacher Complexity (not "empirical")

$$R_m(\mathcal{F}) := \mathbb{E}_{S \sim \mathcal{Z}^m} \hat{R}_S(\mathcal{F})$$

Careful: [SS] uses different terminology:

we'll follow
Mohri

Mohri
et al.

concept

$\hat{R}_S(\mathcal{F})$
"Empirical R.C."

concept

$R_m(\mathcal{F}) = \mathbb{E}_{S \sim \mathcal{Z}^m} \hat{R}_S(\mathcal{F})$
"R.C."

Shalev-Shwartz
+ Ben-David

$R(F \circ S)$
and $F = L \circ H$
"R.C."

$\mathbb{E}_S R(F \circ S)$
(no special notation)
"Expected R.C."

How to use?

Recall for uniform convergence, S was " ϵ -representative" if

$$\sup_{h \in H} |L_D(h) - \hat{L}_S(h)| \leq \epsilon$$

(which implied ERM worked: $L_D(\text{ERM}_H(S)) \leq \epsilon + \min_{h \in H} L_D(h)$)

Something very similar is the "representativeness" of S
(w.r.t. H, L) as

$$\text{Rep}_D((H, L), S) := \sup_{h \in H} \underbrace{\mathbb{E}_{z \sim D} L(h, z)}_{L_D(h)} - \underbrace{\frac{1}{m} \sum_{i=1}^m L(h, z_i)}_{\hat{L}_S(h)}$$

or more generally

$$\underbrace{\Phi(S)}_{\text{in Mohri}} = \text{Rep}_D(F, S) = \sup_{f \in F} \underbrace{\mathbb{E}_{z \sim D} f(z)}_{\mathbb{E}} - \underbrace{\frac{1}{m} \sum_{i=1}^m f(z_i)}_{\hat{\mathbb{E}}_S}$$

want this small
clear $= \sup (\mathbb{E} f - \hat{\mathbb{E}}_S f)$ in shorthand notation.

Intuitively, $\hat{R}_S(F)$ is a reasonable estimate for $\text{Rep}_D(F, S)$

Why? in $\text{Rep}_D(F, S)$ we have $\mathbb{E} f - \hat{\mathbb{E}}_S f$. Split $S = S_1 \cup S_2$ at random

estimate $\mathbb{E} f - \hat{\mathbb{E}}_S f$ by $\underbrace{\hat{\mathbb{E}}_{S_1} f - \hat{\mathbb{E}}_{S_2} f}_{\text{rewrite}}$

Let $S_1 = \{z_i \in [m] : \sigma_i = +1\}$, $S_2 = S \setminus S_1$, and suppose $|S_1| = m/2$ exactly

$$\begin{aligned} \text{then } \hat{\mathbb{E}}_{S_1} f - \hat{\mathbb{E}}_{S_2} f &= \frac{1}{m/2} \sum_{i \in S_1} f(z_i) - \frac{1}{m/2} \sum_{i \in S_2} f(z_i) \\ &= \frac{1}{m/2} \sum_i \sigma_i f(z_i) \end{aligned}$$

Thus taking a $\sup_{f \in F} (\dots)$, as we do in Rep_D and \hat{R}_S ,

we get $\text{Rep}_D(F, S) \approx 2 \cdot \hat{R}_S(F)$

Now, let's be slightly more careful and formalize the above:

Lemma 26.2 (Mohri) $\mathbb{E}_{S \sim \mathcal{D}^m} \text{Rep}_{\mathcal{D}}(\mathcal{F}, S) \leq 2 \cdot \mathbb{E}_{S \sim \mathcal{D}^m} \hat{\mathcal{R}}_S(\mathcal{F})$
 $= 2 \cdot \mathcal{R}_m(\mathcal{F})$.

proof:

$$\begin{aligned}
 \mathbb{E}_{S \sim \mathcal{D}^m} \text{Rep}_{\mathcal{D}}(\mathcal{F}, S) &:= \mathbb{E}_{S \sim \mathcal{D}^m} \sup_{f \in \mathcal{F}} \mathbb{E} f - \mathbb{E}_S^1 f \\
 &= \mathbb{E}_{S \sim \mathcal{D}^m} \sup_{f \in \mathcal{F}} \underbrace{\mathbb{E}_{S' \sim \mathcal{D}^m}}_{\mathbb{E} f} \left(\underbrace{\mathbb{E}_{S'} f}_{\text{no effect}} - \mathbb{E}_S^1 f \right) \\
 &\leq \mathbb{E}_{S, S'} \sup_{f \in \mathcal{F}} \left(\mathbb{E}_{S'}^1 f - \mathbb{E}_S^1 f \right) \quad \text{sup is sub-additive [see details later]} \\
 &:= \mathbb{E}_{S, S'} \sup_{f \in \mathcal{F}} \frac{1}{m} \sum_{i=1}^m f(z_i') - f(z_i) \\
 &= \mathbb{E}_{S, S'} \sup_{f \in \mathcal{F}} \frac{1}{m} \sum_{i=1}^m \sigma_i (f(z_i') - f(z_i)) \\
 &\quad \sigma_i = 1 \text{ ok} \quad \text{for any } \sigma_i \\
 &\quad \sigma_i = -1 \text{ flips } z_i', z_i \dots \text{ but same distribution} \\
 &= \mathbb{E}_{S, S', \sigma} \sup_{f \in \mathcal{F}} \frac{1}{m} \sum_{i=1}^m \sigma_i (f(z_i') - f(z_i)) \quad \text{true } \forall \sigma \text{ so true for } \mathbb{E} \\
 &\leq \mathbb{E}_{S', \sigma} \sup_{f \in \mathcal{F}} \frac{1}{m} \sum_{i=1}^m \sigma_i f(z_i') + \mathbb{E}_{S, \sigma} \sup_{f \in \mathcal{F}} \frac{1}{m} \sum_{i=1}^m \sigma_i (-f(z_i)) \\
 &\quad \text{Sup}(x+y) \leq \text{Sup}(x) + \text{Sup}(y) \\
 &= 2 \mathbb{E}_{S, \sigma} \sup_{f \in \mathcal{F}} \frac{1}{m} \sum_{i=1}^m \sigma_i f(z_i) = 2 \mathbb{E}_S \hat{\mathcal{R}}_S(\mathcal{F}) \\
 &= 2 \mathcal{R}_m(\mathcal{F}) \quad \square
 \end{aligned}$$

sub-additive:

$$\forall a, b \quad g(a, b) \leq \sup_b g(a, b')$$

$$\text{so } \forall b \quad \mathbb{E}_a g(a, b) \leq \mathbb{E}_a \sup_b g(a, b')$$

so

$$\sup_b \mathbb{E}_a g(a, b) \leq \mathbb{E}_a \sup_b g(a, b')$$