

10. Rademacher, part 2

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7:49 PM

Interlude: McDiarmid's Inequality

Thm (McDiarmid)

Let f be a function s.t. $\exists c_i < \infty$ s.t.

$$\forall i \in [m], \quad |f(x_1, \dots, x_i, \dots, x_m) - f(x_1, \dots, x_i', \dots, x_m)| \leq c_i$$

"bounded difference"
for arbitrary (x_1, \dots, x_m) and x_i'

Let $S = (X_1, \dots, X_m)$ ← prob. notation
independent r.v.

Then $\mathbb{P}[f(S) - \mathbb{E}f(S) \geq \varepsilon] \leq \exp\left(\frac{-2\varepsilon^2}{\sum c_i^2}\right)$

$\mathbb{P}[f(S) - \mathbb{E}f(S) \leq -\varepsilon] \leq \text{ " " }$

(in Hoeffding, $f(S) = \sum X_i$... f is linear in S)

Thm (main R.C. generalization bound) Thm 3.3 in Mohri

Let \mathcal{F} be a family of functions from X to $[0, 1]$ (or really $[a, b]$ works)

then $\forall \delta > 0$, w.p. $\geq 1 - \delta$ (w.r.t. $S \sim \mathcal{D}^m$ iid) [any \mathcal{D}]

$$(\forall f \in \mathcal{F}) \quad \underbrace{\mathbb{E} f(z)}_{\text{risk if } f = \text{loh}} - \underbrace{\frac{1}{m} \sum_{i=1}^m f(z_i)}_{\text{empirical risk}} \leq \left\{ \begin{array}{l} \textcircled{A} \quad 2 \mathcal{R}_m(\mathcal{F}) + \sqrt{\frac{\log(1/\delta)}{2m}} \\ \textcircled{B} \quad 2 \hat{\mathcal{R}}_S(\mathcal{F}) + 3 \sqrt{\frac{\log(2/\delta)}{2m}} \end{array} \right\} \left. \begin{array}{l} \text{Right Hand Side} \\ \text{RHS} \end{array} \right\}$$

D shows up here
data dependent (sometimes nice, sometimes not)

(see also Thm. 26.5 in [SS]...)

[SS] usually sets $\text{RHS} = \varepsilon(m)$, solves for $m(\varepsilon)$

which is nice to have but requires many approximations/bounds to make it tractable)

proof Recall $\text{Rep}_{\mathcal{D}}(\mathcal{F}, S) = \sup_{f \in \mathcal{F}} \mathbb{E}_{z \sim \mathcal{D}} f(z) - \frac{1}{m} \sum_{i=1}^m f(z_i)$
← $\mathbb{E}_S f$ shorthand

so by observation, we just need $\text{Rep}_{\mathcal{D}}(\mathcal{F}, S) \leq \text{RHS}$.

Idea: use McDiarmid's, applied to $\text{Rep}_{\mathcal{D}}(\mathcal{F}, S) = \text{Rep}(S)$ drop \mathcal{D}, \mathcal{F} notation since those are fixed

Check the assumptions:

Let $S = S'$ except some $z_i \neq z_i'$

$$\left[\begin{aligned} \text{we'll use } \sup_a g(a) &= \sup_a (g(a) - h(a) + h(a)) \\ &\leq \sup_a (g(a) - h(a)) + \sup_a h(a) \quad \text{like earlier} \end{aligned} \right]$$

$$\begin{aligned} \text{Rep}(S) - \text{Rep}(S') &:= \left(\sup_{f \in \mathcal{F}} \mathbb{E} f - \hat{\mathbb{E}}_S f \right) - \left(\sup_{f \in \mathcal{F}} \mathbb{E} f - \hat{\mathbb{E}}_{S'} f \right) \\ &\leq \sup_{f \in \mathcal{F}} \left(\cancel{\mathbb{E} f} - \hat{\mathbb{E}}_S f \right) - \left(\cancel{\mathbb{E} f} - \hat{\mathbb{E}}_{S'} f \right) \quad \text{via} \\ &= \sup_{f \in \mathcal{F}} \left(\frac{1}{m} (f(z_i') - f(z_i)) \right) \\ &\leq 1 \quad \text{if } f: X \rightarrow [0,1] \\ &\leq 1/m. \end{aligned}$$

So $\forall i \in [m]$, the " c_i " in McDiarmid's is $1/m$

Applying McDiarmid's

$$\mathbb{P}[\text{Rep}(S) - \mathbb{E} \text{Rep}(S) \geq \varepsilon] \leq \exp\left(\frac{-2\varepsilon^2}{\sum_i (1/m)^2}\right) = \exp(-2\varepsilon^2 m) =: \delta$$

Now fix δ , solve for ε

$$-2\varepsilon^2 m = \log(\delta), \quad \varepsilon = \sqrt{-\frac{\log(\delta)}{2m}} = \sqrt{\frac{\log(1/\delta)}{2m}}$$

So w.p. $\geq 1 - \delta$,

$$\text{Rep}(S) \leq \mathbb{E} \text{Rep}(S) + \varepsilon$$

$$\leq 2R_m(\mathcal{F}) + \varepsilon \quad \text{via previous lemma.}$$

which proves (A)

To prove (B), restate (A) using $d/2$:

$$\text{w.p. } \geq 1 - \delta/2, \quad \text{Rep}(S) \leq 2R_m(\mathcal{F}) + \sqrt{\frac{\log(2/\delta)}{2m}} \quad (**)$$

$$\text{Recall } R_m(\mathcal{F}) := \mathbb{E}_S \hat{R}_S(\mathcal{F})$$

write as $\hat{R}(S)$ since \mathcal{F} fixed for now

$$\hat{R}(S) := \mathbb{E}_\sigma \sup_{f \in \mathcal{F}} \frac{1}{m} \sum_{i=1}^m \sigma_i f(z_i)$$

Let's see if we can't apply McDiarmid's again, but this

time the $\mathbb{P}[\dots \leq -\varepsilon] \leq \dots$ side instead of $\mathbb{P}[\dots \geq \varepsilon] \leq \dots$

$$\begin{aligned} \text{Turns out } \hat{R}(S) - \hat{R}(S') &\leq 1/m \quad S = (z_1, \dots, z_m) \\ S' &= (z_1, \dots, z_i', \dots, z_m) \end{aligned}$$

just like for $\text{Rep}(S)$ (only difference is now $\mathbb{E}_{\sigma}(\dots)$ which is linear and doesn't affect anything)

So
 McDiarmid: $\mathbb{P}[\hat{R}(S) - \underbrace{\mathbb{E} \hat{R}(S)}_{R_m} \leq -\varepsilon] \leq \exp(-2\varepsilon^2 m) =: \delta/2$
 i.e. $\mathbb{P}[\hat{R}(S) - R_m(F) > -\varepsilon] \geq 1 - \delta/2$ $\stackrel{\text{So}}{=} \sqrt{\frac{\log(2/\delta)}{2m}}$

So (**)

w.p. $\geq 1 - \delta/2$ $\text{Rep}(S) \leq 2 \cdot R_m(F) + \sqrt{\frac{\log(2/\delta)}{2m}}$

and

w.p. $\geq 1 - \delta/2$ $R_m(F) \leq \hat{R}_S(F) + \sqrt{\frac{\log(2/\delta)}{2m}}$

So combining:

w.p. $\geq 1 - \delta$, $\text{Rep}(S) \leq 2 \hat{R}_S(F) + 3 \cdot \sqrt{\frac{\log(2/\delta)}{2m}}$ (B) \square

Specific Application: Binary classification, 0-1 loss (Lemma 3.4 Mohri)

\mathcal{H} a set of functions (hypotheses) of the form $h: X \rightarrow \mathcal{Y} := \{\pm 1\}$

and use 0-1 loss as usual, $\ell(h, (x, y)) := \mathbb{1}_{h(x) \neq y}$

$S = ((x_1, y_1), \dots, (x_m, y_m))$

$S_x = (x_1, \dots, x_m)$

Observe $\underbrace{\hat{R}_S(\ell \circ \mathcal{H})}_{\text{what we care about}} := \mathbb{E}_{\sigma} \sup_{h \in \mathcal{H}} \frac{1}{m} \sum_{i=1}^m \sigma_i \cdot \mathbb{1}_{h(x_i) \neq y_i}$
 $= \frac{1}{2} \mathbb{E}_{\sigma} \sup_{h \in \mathcal{H}} \frac{1}{m} \sum_{i=1}^m \underbrace{\sigma_i \cdot \mathbb{1}_{h(x_i) \neq y_i}}_{= \frac{1 - y_i \cdot h(x_i)}{2}}$

check:
 $y_i \cdot h(x_i) = \pm 1$
 $+1$ if agree
 -1 else

$= \frac{1}{2} \mathbb{E}_{\sigma} \sup_{h \in \mathcal{H}} \frac{1}{m} \sum_{i=1}^m h(x_i)$

$\mathbb{E} \sigma_i \cdot 1 = 0$
 $\mathbb{E} -\sigma_i y_i = \mathbb{E} \sigma_i y_i$
 $\mathbb{E} \sigma_i y_i \cdot h(x_i) = \mathbb{E} \sigma_i h(x_i)$
 since $y_i \in \{\pm 1\} \Rightarrow \sigma_i y_i \sim \text{Rad.}$

$= \frac{1}{2} \hat{R}_{S_x}(\mathcal{H})$

No reference to labels or loss (0-1 is implicit)
 only \mathcal{H} , D_x

So $\hat{R}_S(\ell \circ \mathcal{H}) = \frac{1}{2} \hat{R}(\mathcal{H})$

and similarly

$R_m(\ell \circ \mathcal{H}) = \frac{1}{2} R_m(\mathcal{H})$

[implicit:
 labels
 $y = f(x_i)$]
 Not agnostic

and now apply our Thm to this case

Thm 3.5 [Mohri] Rademacher Complexity thm for binary classif. w/ 0-1 loss

Let $\mathcal{H} \subseteq \{\pm 1\}^X$, D any distribution X , Then $\forall \delta \in (0, 1)$,

w.p. $\geq 1 - \delta$ (wrt $S_x \sim \mathcal{D}^m$ iid), $\forall h \in \mathcal{H}$

$$L_{\mathcal{D}}(h) \leq L_S(h) + \begin{cases} R_m(\mathcal{H}) + \sqrt{\log(\frac{1}{\delta})} \\ \hat{R}_{S_x}(\mathcal{H}) + 3 \cdot \sqrt{\frac{\log(2/\delta)}{2m}} \end{cases}$$

proof via previous lemma.

Typically $R_m(\mathcal{H}) = O(1/m)$ or $O(1/\sqrt{m})$. Either way,

we're bounding our **estimation error** by $O(1/\sqrt{m})$

so need $m = \Omega(1/\epsilon_{\text{est}}^2)$

$R_m(\mathcal{H})$ is one measure of complexity of \mathcal{H}

Also, we could possibly compute it via optimization:

$$\begin{aligned} \hat{R}_S(\mathcal{H}) &= \mathbb{E}_{\sigma} \sup_{f \in \mathcal{H}} \frac{1}{m} \sum_i \sigma_i f(z_i) \\ &= - \mathbb{E}_{\sigma} \inf_{f \in \mathcal{H}} \frac{1}{m} \sum_i \tilde{\sigma}_i f(z_i) \end{aligned} \quad \tilde{\sigma}_i = -\sigma_i, \text{ both } \sim \text{Rademacher}$$

but at least as hard as solving

$$\inf_{f \in \mathcal{H}} \frac{1}{m} \sum_i f(z_i) = \text{ERM}_{\mathcal{H}}$$

and as we'll see, that's often intractable.

But for simple \mathcal{H} , we can often compute (or at least upper bound) \hat{R}_S or R_m by hand