

MATH466/MATH766

Math of machine learning

Appendix VC Inequality and Error of Binary Classification

References:

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Today's contents:

- VC inequality
- A corollary

Important concepts:

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Recommend reading:

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Binary Classification

\mathcal{H} is a collection of binary classifiers on X

$$\mathcal{H} := \{ h: X \rightarrow \{0,1\} \}$$

$$\text{Risk: } R(h) = \mathbb{E}_{(X,Y) \sim P_{X,Y}} \mathbb{1}_{h(X) \neq Y}$$

$$\text{Emp Risk: } \hat{R}_n(h) = \frac{1}{n} \sum_{i=1}^n \mathbb{1}_{h(X_i) \neq Y_i}, \quad (X_i, Y_i) \sim_{\text{iid}} P_{X,Y}$$

$$\text{Let } \hat{h}_n := \underset{h \in \mathcal{H}}{\operatorname{argmin}} \hat{R}_n(h) \quad (\text{empirical minimizer})$$

$$\text{want to know } \underbrace{R(\hat{h}_n)}_{\text{random}} - \min_{h \in \mathcal{H}} R(h)$$

$$1. \text{ Want to know } \Pr[R(\hat{h}_n) \leq \min_{h \in \mathcal{H}} R(h) + \varepsilon]$$

$$\text{Denote } h^* := \underset{h \in \mathcal{H}}{\operatorname{argmin}} R(h)$$

$$R(\hat{h}_n) - \min_{h \in \mathcal{H}} R(h)$$

$$= (R(\hat{h}_n) - \hat{R}_n(\hat{h}_n)) + \underbrace{(\hat{R}_n(\hat{h}_n) - \hat{R}_n(h^*))}_{\leq 0} + (\hat{R}_n(h^*) - R(h^*))$$

$$\leq |R(\hat{h}_n) - \hat{R}_n(\hat{h}_n)| + |\hat{R}_n(h^*) - R(h^*)|$$

$$\leq 2 \sup_{h \in \mathcal{H}} |\hat{R}_n(h) - R(h)|$$

2. Want to know $\Pr \left[\sup_{h \in \mathcal{H}} |\hat{R}_n(h) - R(h)| \leq \varepsilon \right]$

Denote $\mathcal{A} := \{A_h : h \in \mathcal{H}\}$

where $A_h := \{(x, y) \in \mathcal{X} \times \{0, 1\} : h(x) \neq y\}$

the set of misclassification cases under h

then $R(h) = \Pr[(X, Y) \in A_h \mid (X, Y) \sim P_{X, Y}] =: \mu(A_h)$

$$\hat{R}_n(h) = \frac{1}{n} \sum_{i=1}^n \mathbb{1}_{(X_i, Y_i) \in A_h} =: \mu_n(A_h)$$

Shown in lec 20: $V_{\mathcal{A}} = V_{\mathcal{H}}$

3. Assume $Z \sim P_Z$, $Z_1, Z_2, \dots, Z_n \sim \text{i.i.d. } P_Z$

For a set A , denote $\mu(A) := \Pr[Z \in A]$

$$\mu_n(A) := \frac{1}{n} \sum_{i=1}^n \mathbb{1}_{Z_i \in A}$$

Want to know $\Pr \left[\sup_{A \in \mathcal{A}} |\mu_n(A) - \mu(A)| \leq \varepsilon \right]$

r.v.

4. Bounded Difference Inequality (McDiarmid's inequality)

Def (bounded difference property) $f: \mathcal{Z}_1 \times \mathcal{Z}_2 \times \dots \times \mathcal{Z}_n \rightarrow \mathbb{R}$

$\exists c_1, c_2, \dots, c_n$ s.t.

for all $i = 1, 2, \dots, n$ and all $z_1 \in \mathcal{Z}_1, z_2 \in \mathcal{Z}_2, \dots, z_n \in \mathcal{Z}_n$

$$\sup_{z'_i \in \mathcal{Z}_i} \left| f(z_1, z_2, \dots, z'_i, \dots, z_n) - f(z_1, z_2, \dots, z_i, \dots, z_n) \right| \leq c_i$$

(substituting the i -th coordinate changes the value of f at most c_i)

Thm. Let f satisfies BDP w/ c_1, c_2, \dots, c_n

Z_1, Z_2, \dots, Z_n are independent r.v., $Z_i \in \mathcal{Z}_i$ for all i

Then for any $\varepsilon > 0$

$$\begin{aligned} \Pr [f(Z_1, \dots, Z_n) - \mathbb{E}[f(Z_1, \dots, Z_n)] \geq \varepsilon] \\ \Pr [f(Z_1, \dots, Z_n) - \mathbb{E}[f(Z_1, \dots, Z_n)] \leq -\varepsilon] \end{aligned} \leq \exp \left(- \frac{2\varepsilon^2}{\sum_{i=1}^n c_i^2} \right)$$

In our setting, $c_1 = c_2 = \dots = c_n = \frac{1}{n}$

5. VC inequality

Let $d := V_{\mathcal{A}}$

$$\text{then } \mathbb{E} \left[\sup_{A \in \mathcal{A}} |\mu_n(A) - \mu(A)| \right] \leq 2 \sqrt{\frac{zd \log(2en/d)}{n}}$$

$$\begin{bmatrix} \boxed{4} \\ \boxed{5} \end{bmatrix} - \boxed{3} - \boxed{2} - \boxed{1}$$

With probability $1-\delta$

$$R(\hat{h}_n) \leq \min_{h \in \mathcal{H}} R(h) + 4 \sqrt{\frac{zd \log(2en/d)}{n}} + \sqrt{\frac{\log(2/\delta)}{2n}}$$