

## Chapter 12 Minimax lower bounds

By fundamental theorems of statistical learning

$$\{X, Y=\{0,1\}, \mathcal{F}, P\} \quad \text{Suppose} \quad V = VC(\mathcal{F}) < +\infty$$

$$\text{ERM: } \hat{f}_n = \arg \min_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n 1_{\{f(x_i) \neq y_i\}}$$

$$\text{w.p. } \geq 1-\delta: \quad L(\hat{f}_n) \leq L^*(\mathcal{F}) + C \left( \sqrt{\frac{V}{n}} + \sqrt{\frac{\log(1/\delta)}{n}} \right)$$

$$\underline{\text{Also}} \quad E[L(\hat{f}_n) - L^*(\mathcal{F})] \leq C \sqrt{\frac{V}{n}} \quad (h=0) \quad (C')$$

expected excess risk

$$\underline{\leq} \quad \sup_P E[L(\hat{f}_n) - L^*(\mathcal{F})] \leq C \sqrt{\frac{V}{n}}$$

min max expected excess risk:

$$\hat{f} = A(Z^n) \quad \min \sup_P E[L(\hat{f}_n) - L^*(\mathcal{F})]$$

$$L^*(\mathcal{F}) = \min_{f \in \mathcal{F}} L(f)$$

$$L(f) = P\{Y \neq f(X)\}$$

For  $P$  fixed:

$$\eta(x) = P\{Y=1 | X=x\}$$

$$f^*(x) = \begin{cases} 1 & \text{if } \eta(x) \geq \frac{1}{2} \\ 0 & \text{if } \eta(x) < \frac{1}{2} \end{cases}$$

Deterministic  
label case:  $\eta(x) \in \{0, 1\}$  all  $x$ .

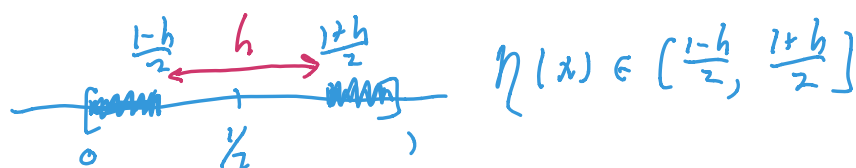
Can be shown  $\sup_P E[L(\hat{f}_n) - L^*] \leq C \frac{V}{n}$  ( $h=1$ )  
in deterministic case

gap between upper bound  $C \frac{V}{n}$

in special case and

$\sqrt{\frac{V}{n}}$  if  $\eta$  is not constrained

Let  $\mathcal{P}(h, \mathcal{F}) = \{P \in \mathcal{P}(\mathcal{F}) : |2\eta(x) - 1| \geq h \text{ a.s.}\}$



$$\text{Let } R_n(h, \mathcal{F}) = \inf_{\hat{f}_n} \sup_{P \in \mathcal{P}(h, \mathcal{F})} E[L(\hat{f}_n) - L(f^*)]$$

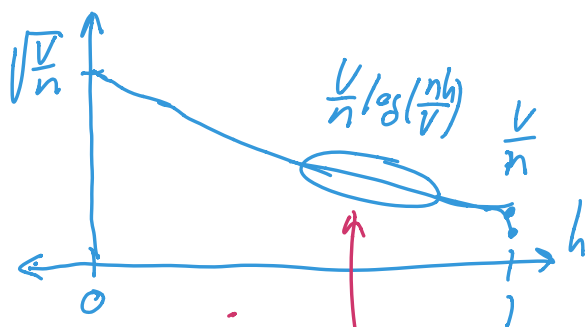
$$\left[ \begin{array}{l} \mathcal{P}(\mathcal{F}) = \text{set of probability dist}^n \text{ on } X \\ \text{such that } f^* \text{ is in } \mathcal{F}, \\ (f_n^* = 1_{\{\eta(x) \geq 1/2\}}, \eta(x) = E(Y|X=x)) \end{array} \right]$$

Theorem 12.1 (we'll prove) ( $c = 1/32$  works)

$$R_n(h, \mathcal{F}) \geq c \min\left(\sqrt{\frac{V}{n}}, \frac{V}{nh}\right)$$

Upper bound:  
on ERM

$$\sup_{P \in \mathcal{P}(h, \mathcal{F})} E[L(\hat{f}_n) - L^*] \leq \begin{cases} c\sqrt{\frac{V}{n}} & \text{if } h \leq \sqrt{\frac{V}{n}} \\ c\frac{V}{nh}(1 + \log(\frac{nh^2}{V})) & \text{if } h > \sqrt{\frac{V}{n}} \end{cases}$$



we have matching lower bound if the sets of classifiers is sufficiently rich (beyond VC dimension)

Why VC dimension may not be enough.

Example A (Fix  $d \geq 1$ )  $(N+ (N, d)$  rich for any  $N \geq d+1$ )

$X = \{1, \dots, d\}$ ,  $\mathcal{F}$  = set of all binary valued functions on  $X$ .

$V_C$  dim. is  $V_C = d$

0010101  
← d →

### Example B

$$X = \mathbb{Z} = \{\dots, -2, -1, 0, 1, 2, \dots\}$$

$\mathcal{F}$  = set of all binary valued functions  
such that  $\sum_{x \in \mathcal{X}} f(x) \leq d$

$f \leftarrow \overbrace{0000000000000000}^{2^0}$

$V = d$   $(I \geq (N, D)$  rich for and  $D$  with  $0 \leq D \leq d$ .

Definition  $(X, Y = \{q_i\}, \mathbb{F}, P)$

Definition

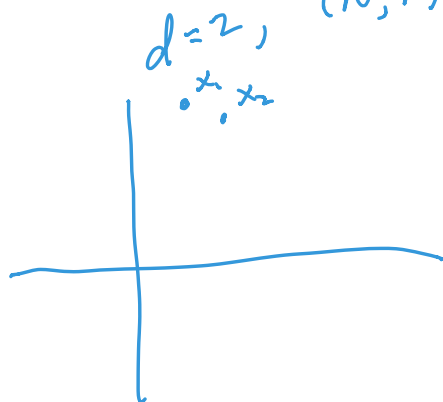
We say  $\mathbb{F}$  is  $(N, D)$  rich for some  $N \geq 1, D \geq 1$  if there exist  $x_1, \dots, x_N \in X$  so that for any length  $N$  binary sequence with  $D$  ones,  $b$  there exists  $f \in \mathbb{F}$  so  $(f(x_1), \dots, f(x_N)) = (b_1, \dots, b_N)$

If  $V = VC$  dimension( $\mathcal{F}$ ) then  
 $\mathcal{F}$  is  $(N, D)$ -rich for any  $D$  with  $0 \leq D \leq V$ .

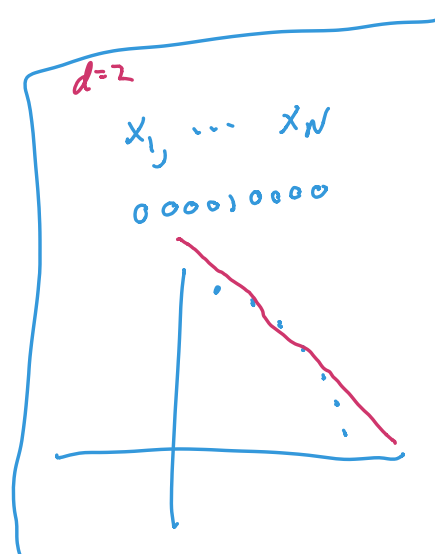
---

Example  $\mathcal{F}$  = set of half spaces with <sup>not necessarily</sup> boundary through the origin in  $\mathbb{R}^d$ .

$VC(\mathcal{F}) = d$   $(N, 1)$  rich



$VC(\mathcal{F}) = d$



(  $\mathcal{F}$  is  $(N, \lfloor d/2 \rfloor)$ -rich for all  $N \geq d+1$  )

Theorem 12.2 Given some  $D \geq 1$ , suppose  
 $\mathcal{F}$  is  $(N, D)$  rich for all  $N \geq 4D$ . Then

$$P_n(h, \mathcal{F}) \geq c(1-h) \frac{D}{nh} \left[ 1 + \log \frac{nh^2}{D} \right]$$