

- Chapter 8 Binary Classification

$(X, \mathcal{Z}, \mathcal{P})$   $\mathcal{P} \in \mathcal{P}$   $\mathcal{P}$  is a prob. dist<sup>n</sup>  
on  $X \times \{0,1\}$  -  $z_i = (x_i, y_i)$

To use the most abstract framework

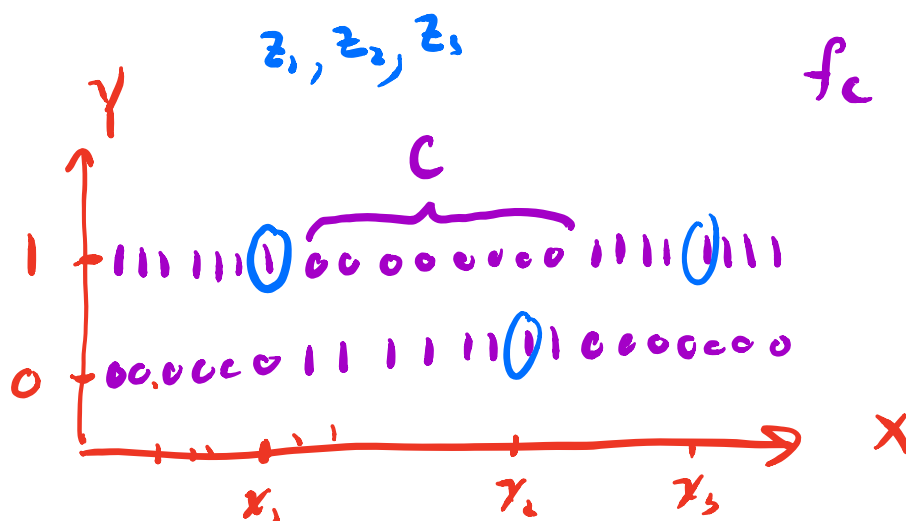
$(\mathcal{Z}, \mathcal{F}, \mathcal{P})$  we let  $f_c(z) = 1_{\{y \neq 1_c(x)\}}$

$$\mathcal{F} = \mathcal{F}_{\mathcal{C}} = \{f_c : c \in \mathcal{C}\}$$

$$E[\Delta(\mathcal{Z}_n)] \leq 2 E[R_n(\mathcal{F}(\mathcal{Z}^n))] \leq 4 \sqrt{\frac{V(\mathcal{F})(n/m)}{n}}$$

Lemma 8.1  $V(\mathcal{C}) = V(\mathcal{F}_{\mathcal{C}})$   $z = (x, y)$

Proof



Thm 8.1

m for Dudley class.

$$L_P(\hat{C}_n) \leq L_P^*(C) + E \sqrt{\frac{VC(L_2(n))}{n}} + \sqrt{\frac{2 \log(1/\delta)}{n}}$$

$\langle W, Z \rangle \leq 30$

eg,  $C = \text{pos}(g+h) = \{z : g(z) + h(z) \geq 0\}$

$$g(z) = \sum_{j=1}^m c_j \psi_j(z)$$

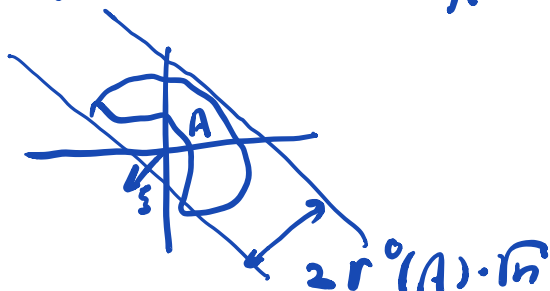
Dudley class  $V(C) = m$

Revisit Rademacher averages

Let  $A \subset \mathbb{R}^n$   
bounded

$$R_n^0(A) = \frac{1}{n} E_{\varepsilon^n} \sup_{a \in A} \sum_{i=1}^n \varepsilon_i a_i$$

$$R_n(A) = \frac{1}{n} E_{\varepsilon^n} \sup_{a \in A} \left| \sum_{i=1}^n \varepsilon_i a_i \right| = R_n(A \cup -A)$$



Contracting principle for  $R_n A$ .

Suppose  $\varphi_i: \mathbb{R} \rightarrow \mathbb{R}$  for  $i \in [n]$

let  $\varphi \circ a = (\varphi_1(a_1), \varphi_2(a_2), \dots, \varphi_n(a_n))$

Suppose  $\varphi_i$  is  $M$ -Lipschitz continuous

$$\text{i.e. } |\varphi_i(a_i) - \varphi_i(a'_i)| \leq M |a_i - a'_i|$$

Let  $\varphi \circ A = \{ \varphi \circ a : a \in A \}$

$$\text{Then } \underline{R_n^\circ(\varphi \circ A)} \leq M R_n^\circ(A)$$

If  $\varphi_i(0) = 0$  for all  $i$  (in addition to above)

$$\text{then } \underline{R_n(\varphi \circ A)} \leq 2M R_n(A) \Leftarrow$$

Proof (6.27) Let  $M=1$  wlog  
Let  $\varphi_j(a_j) = a_j$   $j \neq 1$  wlog

$$\underline{|\varphi_1(a_1) - \varphi_1(a'_1)| \leq |a_1 - a'_1|}$$

$$\begin{array}{lcl} \varepsilon_1 = 1 & \text{w.p.} & \frac{1}{2} \\ -1 & \text{"} & \frac{1}{2} \end{array}$$

$$\begin{aligned}
- R_n^*(A) &= \frac{1}{2n} E \left[ \sup_a \left( a_1 + \sum_{i=2}^n \epsilon_i a_i \right) + \sup_{a'} \left( -a'_1 + \sum_{i=2}^n \epsilon_i a'_i \right) \right] \\
&= \frac{1}{2n} E \left[ \sup_a \sup_{a'} a_1 - a'_1 + \sum_{i=2}^n \epsilon_i a_i + \sum_{i=2}^n \epsilon_i a'_i \right] \\
&= \frac{1}{2n} E \left[ \sup_a \sup_{a'} \underbrace{|a_1 - a'_1|}_{\checkmark} + \sum_{i=2}^n \epsilon_i a_i + \sum_{i=2}^n \epsilon_i a'_i \right] \\
- R_n^*(\varphi_1 \circ A) &= \frac{1}{2n} E \left[ \sup_a \sup_{a'} |\varphi_1(a_1) - \varphi_1(a'_1)| + \sum_{i=2}^n \epsilon_i a_i + \sum_{i=2}^n \epsilon_i a'_i \right] \\
\therefore R_n^*(\varphi_1 \circ A) &\leq R_n^*(A)
\end{aligned}$$

## Ex 2 Binary classification with surrogate loss function

$$(X, P, \text{sgn}(f), l_{0-1}) \quad Z_i = (X_i, Y_i) \text{ i.i.d } P$$

$$g_f(x) = \text{sgn } f(x) = \begin{cases} +1 & \text{if } f(x) \geq 0 \\ -1 & \text{if } f(x) < 0 \end{cases}$$

Loss using  $g_f$  on a fresh sample  $(x, y) \sim P$ .

$$\begin{aligned}
L_P(g_f) &= P(g_f(x) \neq Y) = P(Y g_f(x) \leq 0) \\
&\leq P(Y f(x) \leq 0) = E[1_{\{Y f(x) \leq 0\}}]
\end{aligned}$$

$$\leq E[\varphi(-\gamma f(x))]$$

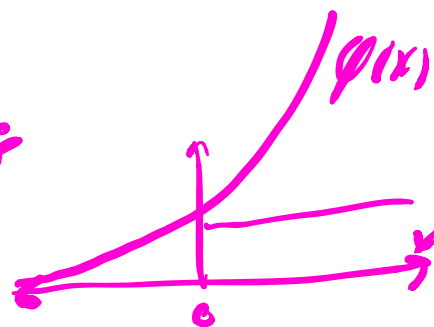
where  $\varphi$  satisfies:

$$\varphi: \mathbb{R} \rightarrow \mathbb{R}$$

1)  $\varphi$  - continuous

2) non decreasing

3)  $\varphi(x) \geq 1_{[x \geq 0]}$



$$l_{\varphi}(\gamma, u) = \varphi(-\gamma u)$$

$$l_{\varphi}(\gamma, u)$$

exponential  $\varphi(x) = e^x$

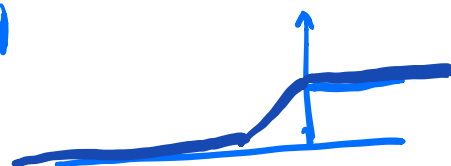
logit  $\log_2(1+e^x)$   $M_{\varphi} = \frac{1}{\ln 2}$



hinge  $(1+x)_+$   $M_{\varphi} = 1$



ramp  $\min[1, (1+x)_+]$   $M_{\varphi} = 1$   
 $\varphi(x/\gamma)$   $M_{\varphi} = 1/\gamma$



Define (fix  $P$ )

$$\left\{ \begin{aligned} A_\varphi(f) &= E_P[\varphi(-Yf(X))] - \varphi(0) \\ A_{\varphi,n}(f) &= \frac{1}{n} \sum_{i=1}^n \varphi(-Y_i f(X_i)) - \varphi(0) \end{aligned} \right. \geq L_P(g_f)$$

$F(x) = \varphi(x) - \varphi(0)$  — has same Lipschitz constant as  $\varphi$ .

Lemma 8.2 Let  $\varphi$  satisfy 1-3  
and suppose  $\varphi(\underline{-yf(x)}) \leq B$  for all  $x, y$   
and  $\varphi$ -Lip( $M_\varphi$ )

Then  $\Delta_n(Z^n) \left( \sup_f |A_\varphi(f) - A_{\varphi,n}(f)| \right)$

$$\leq 4M_\varphi E R_n(F(Z^n)) + \frac{Bt}{\sqrt{n}}$$

with probability at least  $1 - e^{-2t^2}$

$$\frac{\sqrt{2 \log(1/\delta)}}{n}$$

$\int$