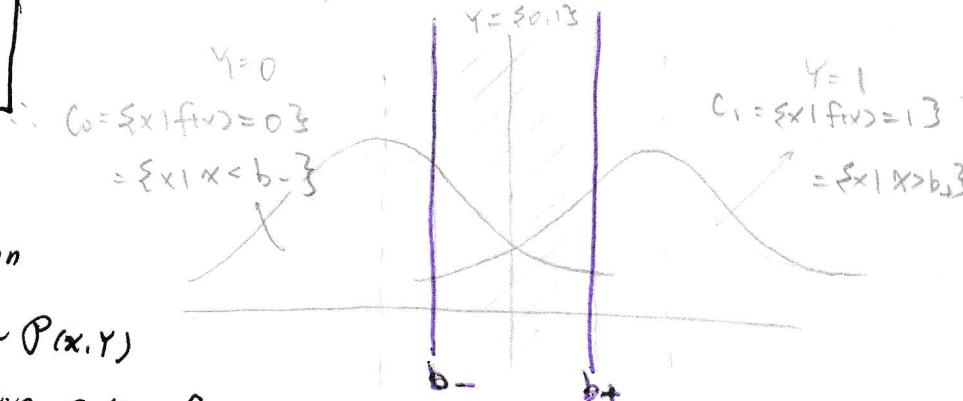


Classification with Confidence



- A New Framework of Classification

$$x \in \mathcal{X}, Y \in \{0, 1\}, (x, Y) \sim P(x, Y)$$

Want to find a classification rule $f(x): \mathcal{X} \rightarrow \{f_0, f_1, f_{0,1}\}$

- define $C_0 = \{x | f(x) = 0\}$

$$C_1 = \{x | f(x) = 1\}$$

$$\left. \begin{array}{l} \\ \end{array} \right\} C_0 \cup C_1 = \mathcal{X}$$

$C_{0,1} = C_0 \cap C_1$ is where the data could be "classified" to $\{0, 1\}$, which called "Ambiguity"

- new question becomes a trade-off b/w classification accuracy and the portion of ambiguity.

→ Want to minimize the ambiguity portion w/ a control on accuracy, i.e.

Given $P_0(C_0) = P(X \in C_0 | Y=0) \geq 1 - \alpha_0$

$$P_1(C_1) = P(X \in C_1 | Y=1) \geq 1 - \alpha_1 \quad \begin{matrix} \leftarrow \\ \text{accuracies} \end{matrix}$$

and $C_0 \cup C_1 = \mathcal{X}$

(*)
↑
target

Want to minimize

$$P(C_0 \cap C_1) = \pi_0 P_0(C_0 \cap C_1) + \pi_1 P_1(C_0 \cap C_1)$$

$$\pi_j = P(Y=j) \quad j=0,1$$

- Thm 1 gives a solution to probt the target problem (*)

Thm 1 says, fix $0 < \alpha_0, \alpha_1 < 1$ a solution to (*) is given by

$$C_0 = \{x : \eta(x) \leq t_0(\alpha_0)\}, \quad C_1 = \{x : \eta(x) \geq t_1(\alpha_1)\} \cup C_0^c$$

where t_0 and t_1 are chosen s.t.

$$P_0(\eta(x) \leq t_0(\alpha_0)) = 1 - \alpha_0, \quad P_1(\eta(x) \geq t_1(\alpha_1)) = 1 - \alpha_1$$

- quick proof of Thm 1.

Proof:

WLOG, assume $t_0 \geq t_1$



a.w.
 $C_{0,1} = \emptyset$

Suppose we have a new classifier $f^*(x)$ w/

$$S_0 = \{x \mid f^*(x) = 0\}, P_0(S_0) \geq 1 - \alpha_0$$

$$S_1 = \{x \mid f^*(x) = 1\}, P_0(S_1) \geq 1 - \alpha_1$$

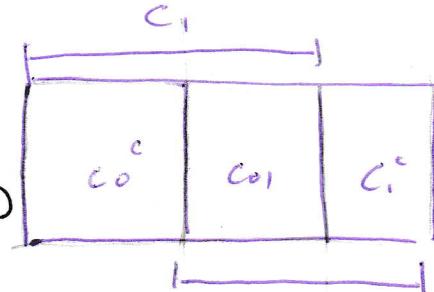
$$S_{0,1} = S_0 \cap S_1$$

want to show

$$P_0(C_{0,1}) \leq P_0(S_{0,1})$$

$$\therefore P_0(C_0) \leq P_0(S_0)$$

$$\Rightarrow P_0(C_0^c \cup C_{0,1}) \leq P_0(S_0 \cap C_0) + P_0(S_0 \cap C_0^c)$$



$$\Rightarrow P_0[(C_0^c \cup C_{0,1}) \cap S_0] + P_0[(C_0^c \cup C_{0,1}) \cap S_0^c] \leq P_0[(C_{0,1} \cup C_1^c) \cap S_0] + P_0(S_0 \cap C_0^c)$$

$$\Rightarrow P_0(C_0^c \cap S_0) + P_0(C_{0,1} \cap S_0) + P_0(C_1^c \cap S_0^c) + P_0(C_0 \cap S_0^c)$$

$$\leq P_0(C_{0,1} \cap S_0) + P_0(C_1^c \cap S_0) + P_0(S_0 \cap C_0^c)$$

$S_{0,1} \cup S_1^c$

$$\Rightarrow P_0(C_0^c \cap S_0^c) + P_0(C_{0,1} \cap S_0^c) \leq P_0(S_0 \cap C_0^c) + P_0(S_1^c \cap C_0^c)$$

$$\Rightarrow P_0(C_{0,1} \cap S_0^c) - P_0(C_0^c \cap S_{0,1}) \leq P_0(S_1^c \cap C_0^c) - P_0(S_0^c \cap C_{0,1}) \quad (**)$$

$$\therefore P_0(C_{0,1}) - P_0(S_{0,1})$$

$$= P_0(C_{0,1} \cap S_1^c) + P_0(C_{0,1} \cap S_0^c) - P_0(C_0^c \cap S_{0,1}) - P_0(C_1^c \cap S_{0,1})$$

L.H.S. of (**)

$$\leq P_0(C_{0,1} \cap S_1^c) + P_0(S_1^c \cap C_0^c) - P_0(S_0^c \cap C_{0,1}) - P_0(C_1^c \cap S_{0,1})$$

$$= P_0(C_1 \cap S_1^c) - P_0(S_1 \cap C_1^c)$$

$$\therefore P_0(C_{01}) - P_0(S_{01}) \leq P_0(C_1 \cap S_1^c) - \underbrace{P_0(S_1 \cap C_1^c)}$$

$\eta(x) \geq t_0(\alpha_1)$
in this set

$\eta(x) \leq t_0(\alpha_0)$ in this set
 ~~$\forall x \in C_1^c \Rightarrow x \notin C_0$~~

If we consider a discrete X

$$\therefore \text{for } \forall x \in C_1 \cap S_1^c, \frac{P(Y=1 | X=x)}{P(Y=0 | X=x)} = \frac{\eta}{1-\eta} \geq \frac{t_1(\alpha_1)}{1-t_1(\alpha_1)}$$

//

$$\frac{P(Y=1, X=x) / P(X=x)}{P(Y=0, X=x) / P(X=x)} = \frac{P(Y=1, X=x) / P(Y=1)}{P(Y=0, X=x) / P(Y=0)} \cdot \frac{\frac{P(Y=1)}{P_0(Y=1)}}{\frac{P(Y=0)}{P_0(Y=0)}}$$

$$= \frac{P_1(x)}{P_0(x)} \cdot \frac{\pi_1}{\pi_0} \geq \frac{t_1}{1-t_1}$$

$$\Rightarrow P_0(X) \leq \frac{1-t_1}{t_1} \cdot \frac{\pi_1}{\pi_0} P_1(X)$$

$$\therefore P_0(C_1 \cap S_1^c) \leq \frac{1-t_1}{t_1} \cdot \frac{\pi_1}{\pi_0} P_1(C_1 \cap S_1^c)$$

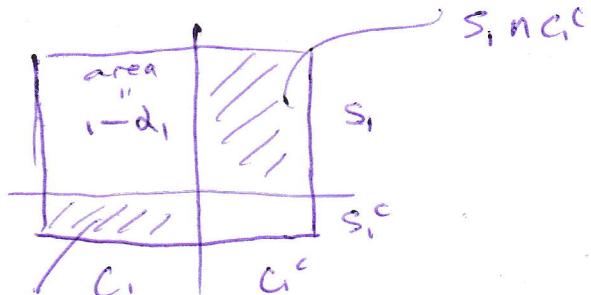
Similarly ~~$P_0(S_1 \cap C_1^c)$~~ $P_0(S_1 \cap C_1^c) \leq \frac{1-t_1}{t_1} \cdot \frac{\pi_1}{\pi_0} P_1(S_1 \cap C_1^c)$

$$\therefore P_0(C_{01}) - P_0(S_{01}) \leq \frac{\pi_1}{\pi_0} \frac{1-t_1}{t_1} [P_1(C_1 \cap S_1^c) - P_1(S_1 \cap C_1^c)]$$

$$\therefore P_0(C_{01}) - P_0(S_{01}) \leq 0$$

b/c

$$P_1(C_1 \cap S_1^c) \leq P_1(S_1 \cap C_1^c)$$



$C_1 \cap S_1^c$

$$P_1(C_1 \cap S_1^c) \leq P_1(C_1 \cap S_1)$$

• If η is estimated by $\hat{\eta}$,

then classifications can be estimated as

$$\hat{C}_0 = \{x : \hat{\eta}(x) \leq \hat{t}_0(\alpha_0)\} \quad \hat{C}_1 = \{x : \hat{\eta}(x) \geq \hat{t}_1(\alpha_1)\} \cup \hat{C}^c$$

estimate to and t_i depends
on how to model the data

If order all $\hat{\eta}(x_i)$'s, then α_0, α_1 can get controlled by choosing sample quantiles.

- Want the estimate $\hat{\eta}$ to be good!

- If G_i is c.d.f. of $\eta(x)$ under P_i :

(***) want $b_1|\varepsilon|^\delta \leq |G_i(t_i + \varepsilon) - G_i(t_i)| \leq b_2|\varepsilon|^\delta$

G_i should be ↗

Smooth at true t_i 's

• (δ_n, p_n) accuracy

An estimator $\hat{\eta}$ is (δ_n, p_n) accurate if $P(|\hat{\eta} - \eta| \geq \delta_n) \leq p_n$

• Thm 2

If $\hat{\eta}$ is (δ_n, p_n) -accurate and condition (***)) holds, then for each $r > 0$, \exists a positive constant C s.t.

$$P_j(\hat{C}_j \Delta C_j) \leq C \left\{ \delta_n^\nu + \left(\frac{\log n}{n} \right)^{\frac{1}{2}} \right\}, \quad j=0,1$$

w/ probability at least $1 - p_n - nr$

i.e. L1-Penalized logistic regression gives $\delta_n - p_n$ accurate estimator