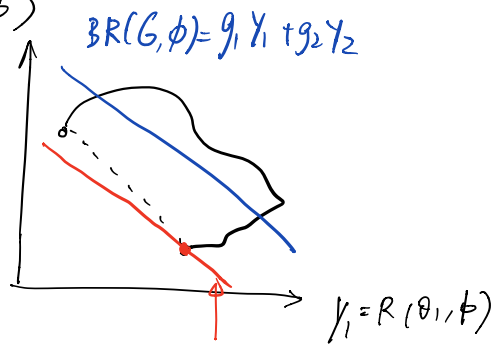


- Bayes Risk

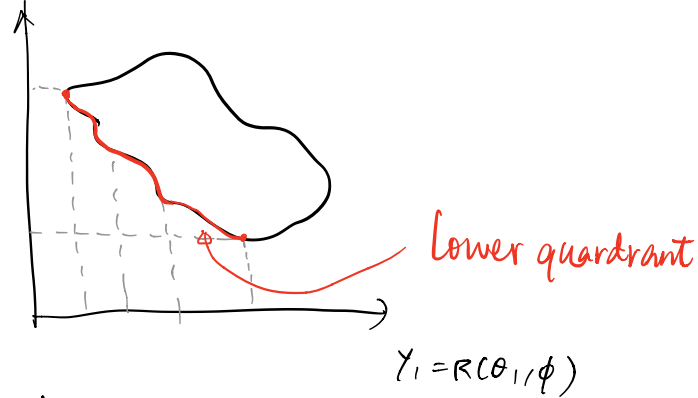
$$Y_2 = R(\theta_2, \phi)$$



- Lower quadrant

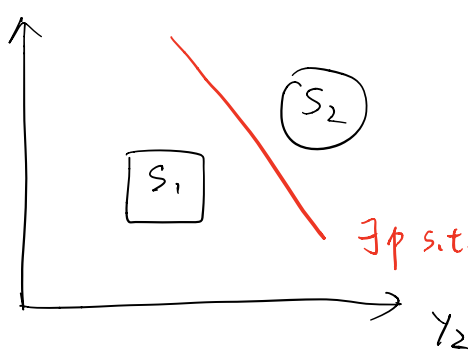
~~*~~ Bayes Risk function w.r.t. G

$$Y_2 = R(\theta_2, \phi)$$



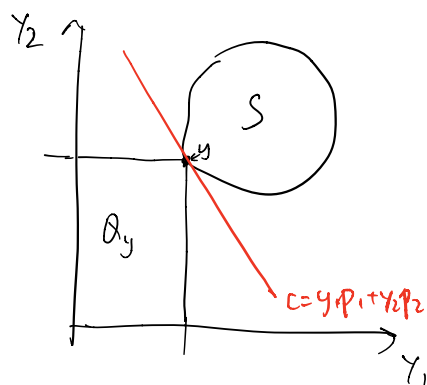
- Separating Hyper plane

$$Y_2$$



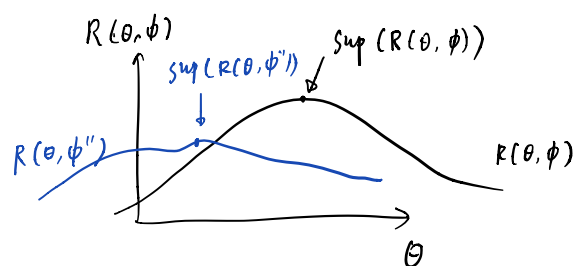
$\exists p$ s.t. $\sum_{i=1}^n p_i x_i \leq \sum_{i=1}^n p_i y_i$ where $x \in S_1$
 $y \in S_2$

- Construct Bayes' Rule from Admissible Rule



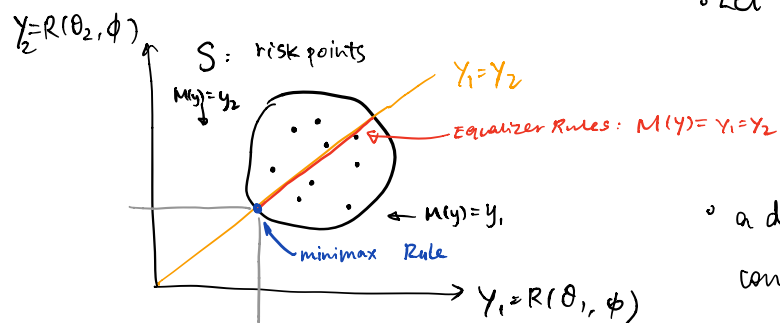
- $Q_y \setminus \{y\}$ is convex
 - ϕ is admissible $\Rightarrow S \cap Q_y = \{y\}$
 - $Q_y \setminus \{y\}$ and S are disjoint
- \Rightarrow By Separating Hyperplane Theorem,
 $\exists c = \gamma_1 p_1 + \gamma_2 p_2$ that is Bayes' Rule.

- Minimax decision Rule.



$$\sup_{\theta \in \Theta} R(\theta, \phi) = \inf_{\phi \in D^*} \sup_{\theta \in \Theta} R(\theta, \phi')$$

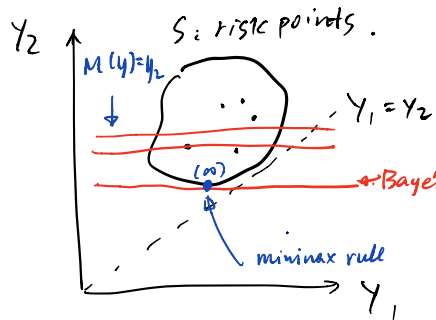
- Equalizer Rule



• Let $M(y) = \max \{\gamma_1, \gamma_2\}$

- a decision rule $\phi \in D^*$ has a constant risk function

- Theorem 85:



• Let $G = (0, 1)$

• $BR(G, \phi) = R(\theta_2, \phi) = y_2$

$$BR(G, (x)) = y_2 \text{ of } (x)$$

$$\geq \max_{i=1,2} R(\phi_i, x)$$

$$= \max \{y_1, y_2 \text{ of } (x)\}$$