

2. Consider a decision problem with a parameter space Θ having a finite number of values, $\theta_1, \dots, \theta_l, l < \infty$.

- ✓(a) Show that a Bayes rule d_B with respect to a prior distribution Λ on Θ having positive probabilities $\lambda_1, \dots, \lambda_l > 0$ is admissible.
- * (b) The result in part (a) conflicts with other results for continuous parameter spaces where Bayes rules may not be admissible, eg, James-Stein estimation. In the discrete case described above, show that if $\lambda_i = 0$, some $i = 1, \dots, l$, then the resulting Bayes rule d_B may not be admissible.
- ✓(c) Suppose that the frequentist risk of d_B in part (b) is finite and constant on those θ_i 's having $\lambda_i > 0$. Show that this decision rule is minimax, that is, minimizes the maximum risk, on those θ_i 's with $\lambda_i > 0$.
- ✓(d) Can anything be said about whether or not d_B in part (b) is minimax on $\theta_i, i = 1, \dots, l$? Discuss.

In (e), (f), and (g), consider the following classification problem. Suppose that X is an observation from the density

$$p(x|\theta) = \theta^{-1}I(0 < x < \theta),$$

where $I(\cdot)$ denotes the indicator function and the parameter space is $\Theta = \{1, 2, 3\}$. It is desired to classify X as arising from $p(x|1)$, $p(x|2)$, or $p(x|3)$, under a 0-1 loss function (zero loss for a correct decision, a loss of one for an incorrect decision).

- 701
HW2
#5
- ✓(e) Find the form of the Bayes rule for this problem.
- ✓(f) Find the decision rule which minimizes the maximum risk over Θ and the corresponding least favorable prior distribution.
- (g) Find the decision rule which minimizes the maximum risk over $\theta = 1$ and $\theta = 2$ and the corresponding least favorable prior distribution. Is this minimax rule the same as that in (f)? Explain.

admissibility

Bayes risk

Bayes rule

minimax

Form of Bayes rule - classification

Find minimax & least favorable prior

a) Proof Assume d_B inadmissible.

$$\Rightarrow \exists d \text{ s.t. } \forall \theta_i \in \Theta$$

$$R(\theta_i, d) \leq R(\theta_i, d_B)$$

$$\text{and } \exists \theta_j \in \Theta \text{ s.t.}$$

$$R(\theta_j, d) < R(\theta_j, d_B).$$

$$\Rightarrow \sum_{i=1}^L \lambda_i R(\theta_i, d) < \sum_{i=1}^L \lambda_i R(\theta_i, d_B)$$

$$\Rightarrow R(\Lambda, d) < R(\Lambda, d_B)$$

contradicts d_B as Bayes rule

$\Rightarrow d_B$ admissible. └

b) $\lambda_i = 0$ for some $i = 1, \dots, L \Rightarrow$ Bayes rule may not be admissible

WTS a Bayes rule can be inadmissible

Proof

~~Let d_B be Bayes rule and a some other rule~~

~~$$\Rightarrow R(\Lambda, d_B) < R(\Lambda, d)$$~~

~~$$\Rightarrow \sum_{i=1}^L \lambda_i R(\theta_i, d_B) < \sum_{i=1}^L \lambda_i R(\theta_i, d)$$~~

Let d_B be such that

$$R(\theta_i, d_B) > R(\theta_i, d) \text{ for some } i$$

and

$$R(\theta_j, d_B) \leq R(\theta_j, d)$$

suppose d_B inadmissible.

$$\Rightarrow \exists d \text{ s.t. } \forall \theta_i \in \Theta$$

$$R(\theta_i, d) \leq R(\theta_i, d_B)$$

$$\text{and } \exists \theta_j \in \Theta \text{ s.t.}$$

$$R(\theta_j, d) < R(\theta_j, d_B).$$

b) cont'd

suppose $R(\theta_j, d) < R(\theta_j, d_B)$ for some $j \in 1, \dots, \ell$
 and $R(\theta_i, d) = R(\theta_i, d_B)$ for all other i

Let $\lambda_j = 0$

$$\Rightarrow \sum_{i=1}^{\ell} \lambda_i R(\theta_i, d) = \sum_{i=1}^{\ell} \lambda_i R(\theta_i, d_B)$$

$$\Rightarrow R(\Lambda, d) = R(\Lambda, d_B)$$

\Rightarrow does not contradict d_B Bayes rule, just shows not unique.

c) Recall minimax

$$\sup_{\theta} R(\theta_i, d_B) < \sup_{\theta} R(\theta_i, d)$$

Proof

We are given that frequentist risk of d_B is finite & constant on those θ_i 's having $\lambda_i > 0$. Let r be this constant risk

$$\Rightarrow R(\Lambda, d_B) = \sum_{i=1}^{\ell} \lambda_i R(\theta_i, d_B) = \sum_{i=1}^{\ell} \lambda_i r = r \sum_{i=1}^{\ell} \lambda_i = r$$

Assume d_B not minimax on those θ_i 's with $\lambda_i > 0$.

That is, $\exists d^*$ s. t.

$$\sup_{\theta} R(\theta_i, d^*) < \sup_{\theta} R(\theta_i, d_B)$$

$$\Rightarrow \sup_{\theta} R(\theta_i, d^*) < r$$

$$\Rightarrow R(\Lambda, d^*) = \sum_{i=1}^{\ell} \lambda_i R(\theta_i, d^*) < \sum_{i=1}^{\ell} \lambda_i r = r$$

\Rightarrow contradicts d_B as Bayes rule

$\Rightarrow d_B$ is minimax on these θ_i 's.

d) For i where $\lambda_i = 0$, it is possible that
 $R(\theta_i, d_B) > R(\theta_i, d)$ for some $d \in \mathcal{D}$

and

$$R(\theta_j, d_B) = R(\theta_j, d) \text{ for all other } j=1, \dots, e$$

We are not given that the frequentist risk is finite & constant at θ_i .

\Rightarrow It is possible that

$$\sup_{\theta} R(\theta_i, d_B) > \sup_{\theta} R(\theta_i, d)$$

When d_B not admissible

$\Rightarrow d_B$ not minimax.

e) $p(x|\theta) = \theta^{-1} I(0 < x < \theta)$

0-1 loss

$$p(\theta|x) \propto p(x|\theta) \lambda(\theta)$$

$$\Theta = \{1, 2, 3\}$$

Bayes rule minimizes posterior expected loss.

$$p(x|1) = I(0 < x < 1)$$

$$p(x|2) = \frac{1}{2} I(0 < x < 2)$$

$$p(x|3) = \frac{1}{3} I(0 < x < 3)$$

Let λ_i be prior probability for θ_i , $\lambda_1 + \lambda_2 + \lambda_3 = 1$

If $x \geq 2 \Rightarrow d_A(x) = 3$

Let $\phi_i(x)$ be probability of action

$\phi_3(x)=1, \phi_1(x)=\phi_2(x)=0$ given observation x .

If $x \geq 1 \Rightarrow$ we need some randomization between 2 & 3.

$\phi_1(x) = 0$

$$\lambda_2 p(x|2) > \lambda_3 p(x|3)$$

$$\phi_2(x) = I\left(\frac{3}{2}\lambda_2 > \lambda_3\right) + \sigma_1 I\left(\frac{3}{2}\lambda_2 = \lambda_3\right)$$

$$\lambda_2 \frac{1}{2} > \lambda_3 \frac{1}{3}$$

$$\frac{3}{2}\lambda_2 > \lambda_3$$

$$\phi_3(x) = I\left(\frac{3}{2}\lambda_2 < \lambda_3\right) + (1-\sigma_1) I\left(\frac{3}{2}\lambda_2 = \lambda_3\right)$$

cases

$$\frac{3}{2}\lambda_2 > \lambda_3 \Rightarrow \phi_2(x) = 1, \phi_3(x) = 0$$

$$\phi_2(x) = \sigma_1 I\left(\frac{3}{2}\lambda_2 = \lambda_3\right)$$

$$\frac{3}{2}\lambda_2 < \lambda_3 \Rightarrow \phi_2(x) = 0, \phi_3(x) = 1$$

$$\Rightarrow \phi_3(x) = 1 - \sigma_1$$

$$\frac{3}{2}\lambda_2 = \lambda_3 \Rightarrow \text{randomization needed}$$

e) more details

Bayes rule minimizes posterior expected loss

~~$$E_{\theta|x} [L(\theta, a_1)]$$~~

$$E_{\theta|x} [L(\theta, 1)] = \frac{\lambda_2}{2} + \frac{\lambda_3}{3}$$

$$E_{\theta|x} [L(\theta, 2)] = \lambda_1 + \frac{\lambda_3}{3}$$

$$E_{\theta|x} [L(\theta, 3)] = \lambda_1 + \frac{\lambda_2}{2}$$

consider

$$0 < x < 1$$

$$\text{If } \frac{\lambda_2}{2} + \frac{\lambda_3}{3} < \lambda_1 + \frac{\lambda_3}{3}$$

$$\Rightarrow \phi_1(x) = 1$$

$$\frac{\lambda_2}{2} + \frac{\lambda_3}{3} < \lambda_1 + \frac{\lambda_2}{2}$$

$$\Rightarrow \left. \begin{array}{c} \lambda_1 > \frac{\lambda_2}{2} \\ \text{or} \\ \lambda_1 > \frac{\lambda_3}{3} \end{array} \right\} \text{equivalent to previous page.}$$

e) cont'd

$$\boxed{\text{If } 0 < x < 1}$$

$$\lambda_1 p(x|1) > \lambda_2 p(x|2)$$

$$\lambda_1 > \frac{1}{2} \lambda_2$$

cases

$$\lambda_1 > \frac{1}{2} \lambda_2 \quad \vee \quad \lambda_1 > \frac{1}{3} \lambda_3 \Rightarrow \begin{aligned} \phi_1(x) &= 1 \\ \phi_2(x) &= \phi_3(x) = 0 \end{aligned}$$

$$\frac{1}{2} \lambda_2 > \lambda_1 \quad \vee \quad \frac{1}{2} \lambda_2 > \frac{1}{3} \lambda_3 \Rightarrow \begin{aligned} \phi_2(x) &= 1 \\ \phi_1(x) &= \phi_3(x) = 0 \end{aligned}$$

$$\frac{1}{3} \lambda_3 > \lambda_1 \quad \vee \quad \frac{1}{3} \lambda_3 > \frac{1}{2} \lambda_2 \Rightarrow \begin{aligned} \phi_3(x) &= 1 \\ \phi_1(x) &= \phi_2(x) = 0 \end{aligned}$$

$$\lambda_1 = \frac{1}{2} \lambda_2 \quad \vee \quad \lambda_1 > \frac{1}{3} \lambda_3 \Rightarrow \begin{aligned} \phi_3(x) &= 0 \\ \phi_1(x) &= \sigma_2 \\ \phi_2(x) &= 1 - \sigma_2 \end{aligned}$$

$$\lambda_1 = \frac{1}{3} \lambda_3 \quad \vee \quad \lambda_1 > \frac{1}{2} \lambda_2 \Rightarrow \begin{aligned} \phi_2(x) &= 0 \\ \phi_1(x) &= \sigma_3 \\ \phi_3(x) &= 1 - \sigma_3 \end{aligned}$$

$$\frac{1}{2} \lambda_2 = \frac{1}{3} \lambda_3 \quad \vee \quad \frac{1}{2} \lambda_2 > \lambda_1 \Rightarrow \begin{aligned} \phi_1(x) &= 0 \\ \phi_2(x) &= \sigma_4 \\ \phi_3(x) &= 1 - \sigma_4 \end{aligned}$$

$$\lambda_1 = \frac{1}{2} \lambda_2 = \frac{1}{3} \lambda_3 \Rightarrow \begin{aligned} \phi_1(x) &= \sigma_5 \\ \phi_2(x) &= \sigma_6 \\ \phi_3(x) &= 1 - \sigma_5 - \sigma_6 \end{aligned}$$

$$\begin{aligned} \phi_1(x) &= \mathbb{I}(\lambda_1 > \frac{1}{2} \lambda_2) \mathbb{I}(\lambda_1 > \frac{1}{3} \lambda_3) + \sigma_2 \mathbb{I}(\lambda_1 = \frac{1}{2} \lambda_2) \mathbb{I}(\lambda_1 > \frac{1}{3} \lambda_3) \\ &+ \sigma_3 \mathbb{I}(\frac{1}{3} \lambda_3 = \lambda_1) \mathbb{I}(\lambda_1 > \frac{1}{2} \lambda_2) + \sigma_5 \mathbb{I}(\lambda_1 = \frac{1}{2} \lambda_2) \mathbb{I}(\lambda_1 = \frac{1}{3} \lambda_3) \end{aligned}$$

$$\begin{aligned} \phi_2(x) &= \mathbb{I}(\frac{1}{2} \lambda_2 > \lambda_1) \mathbb{I}(\frac{1}{2} \lambda_2 > \frac{1}{3} \lambda_3) + (1 - \sigma_2) \mathbb{I}(\lambda_1 = \frac{1}{2} \lambda_2) \mathbb{I}(\lambda_1 > \frac{1}{3} \lambda_3) \\ &+ \sigma_4 \mathbb{I}(\frac{1}{2} \lambda_2 = \frac{1}{3} \lambda_3) \mathbb{I}(\frac{1}{2} \lambda_2 > \lambda_1) + \sigma_6 \mathbb{I}(\lambda_1 = \frac{1}{2} \lambda_2) \mathbb{I}(\lambda_1 = \frac{1}{3} \lambda_3) \end{aligned}$$

$$\begin{aligned} \phi_3(x) &= \mathbb{I}(\frac{1}{3} \lambda_3 > \lambda_1) \mathbb{I}(\frac{1}{3} \lambda_3 > \frac{1}{2} \lambda_2) + (1 - \sigma_3) \mathbb{I}(\lambda_1 = \frac{1}{3} \lambda_3) \mathbb{I}(\lambda_1 > \frac{1}{2} \lambda_2) \\ &+ (1 - \sigma_4) \mathbb{I}(\frac{1}{2} \lambda_2 = \frac{1}{3} \lambda_3) \mathbb{I}(\frac{1}{2} \lambda_2 > \lambda_1) + (1 - \sigma_5 - \sigma_6) \mathbb{I}(\lambda_1 = \frac{1}{2} \lambda_2) \mathbb{I}(\lambda_1 = \frac{1}{3} \lambda_3) \end{aligned}$$

f) want constant risk for Bayes rule to get minimax
 $R(\theta_i, \phi) = 1 - E_{\theta_i}[\phi_i] = \text{constant}$

Now

$$E_{\theta_3}[\phi_3(x)] \geq E_{\theta_3}[I(2 \leq x \leq 3)] \\ = P(2 \leq x \leq 3) \geq 0$$

$$\Rightarrow R(\theta_3, \phi) \text{ constant}$$

For

$$E_{\theta_1}[\phi_1(x)] = E_{\theta_2}[\phi_2(x)] = E_{\theta_3}[\phi_3(x)]$$

it is best to look at a case that occurs in all 3 rules

$$\Rightarrow \lambda_1 = \frac{\lambda_2}{2} = \frac{\lambda_3}{3}$$

$$\Rightarrow \lambda_1 = \frac{\lambda_2}{2}$$

$$\lambda_1 = \frac{\lambda_3}{3}$$

$$\lambda_1 + \lambda_2 + \lambda_3 = 1$$

$$\Rightarrow \lambda_1 + 2\lambda_1 + 3\lambda_1 = 1$$

$$\Rightarrow 6\lambda_1 = 1 \Rightarrow$$

\Rightarrow

$$\lambda_1 = \frac{1}{6}$$

$$\lambda_2 = \frac{1}{3}$$

$$\lambda_3 = \frac{1}{2}$$

Least favorable prior

\Rightarrow

$$\phi_1(x) = \sigma_5 I(0 < x < 1)$$

$$\phi_2(x) = \sigma_1 I(1 \leq x < 2) + \sigma_6 I(0 < x < 1)$$

$$\phi_3(x) = I(2 \leq x < 3) + (1 - \sigma_1) I(1 \leq x < 2) + (1 - \sigma_5 - \sigma_6) I(0 < x < 1)$$

Minimax rule.

g)

want

$$E_{\theta_1}[\phi_1(x)] = E_{\theta_2}[\phi_2(x)]$$

look for cases that occur in ~~at~~ both

$$\lambda_1 = \frac{\lambda_2}{2} \quad \text{let } \lambda_3 = 0$$

$$\Rightarrow \lambda_1 + \lambda_2 = 1$$

$$\Rightarrow \lambda_1 + 2\lambda_1 = 1$$

$$\Rightarrow 3\lambda_1 = 1 \Rightarrow \lambda_1 = \frac{1}{3}$$

$$\lambda_2 = \frac{2}{3}$$

$$\Rightarrow \phi_1(x) = [\tau_2] I(0 < x < 1)$$

$$\phi_2(x) = I(1 \leq x < 2) + (1 - \tau_2) I(0 < x < 1)$$

$$\phi_3(x) = I(2 \leq x < 3)$$

$\lambda_1 = \frac{1}{3}$
$\lambda_2 = \frac{2}{3}$
$\lambda_3 = 0$

Least
favorable
prior

not the same
as (f).