

## HW 2

1. Consider a decision problem with  $D = \{d_1, d_2\}$ ,  $\Theta = \{0, 1\}$  and sample space  $\mathcal{X} = \{1, 2\}$ . Suppose  $f_0(1) = 1/2$  and  $f_1(1) = 1/3$  and the loss function is give by the table

	$\theta = 0$	$\theta = 1$
$d_1$	1	3
$d_2$	4	2

Suppose the non-randomized decision function

$$\delta = (\delta(1) = d_i, \delta(2) = d_j)$$

is represented by  $(i, j)$  then the four non-randomized decision functions are  $(1,1)$ ,  $(1,2)$ ,  $(2,1)$  and  $(2,2)$ .

i) Show that every behavioral decision function is a randomized decision function.

ii) Evaluate the risk vector for each of the four non-randomized decision functions and graph the risk set.

iii) For any prior  $\pi = P(\theta = 0)$  find a Bayes rule against  $\pi$ .

2. Consider a decision problem with  $D = [0, 1]$ ,  $\Theta = \{0, 1\}$  and sample space  $\mathcal{X} = \{1, 2\}$ . Let  $f_\theta(1) = (1+\theta)/3$ , and  $L(0, d) = d^2$  and  $L(1, d) = 1-d$ . For any prior  $\pi = P(\theta = 0)$  find a Bayes rule, graph the lower boundary of the risk set and find a minimax rule.

3. Let  $X$  be binomial( $n, \theta$ ) where  $n$  is known and  $\theta \in \Theta = (0, 1)$  is unknown. Let  $D = [0, 1]$  and  $L(\theta, d) = (\theta - d)^2$ .

i) Show that  $\delta(X) = X/n$  is not a Bayes estimator of  $\theta$ .

ii) Show that  $\delta$  is the unique Bayes estimator of  $\theta$  when the loss function is  $L(\theta, d) = (\theta - d)^2/(\theta(1 - \theta))$  and the prior distribution for  $\theta$  is the uniform distribution.

4. Let  $\Theta = (0, 1]$ ,  $D = [0, 1]$  and

$$L(\theta, d) = \min \left\{ \frac{(\theta - d)^2}{\theta^2}, 2 \right\}$$

Let  $X$  be binomial( $n, \theta$ ) where  $n$  is known. Show that the rule  $\delta^*(x) = 0$  for  $x = 0, 1, \dots, n$  is the unique minimax decision rule.

5. Let  $X$  be a random variable with two possible density functions  $f_{\theta_1}(\cdot)$  and  $f_{\theta_2}(\cdot)$ . Let  $\pi = P(\theta = \theta_1)$  be the prior probability for  $\theta_1$  and  $\pi(x) = P(\theta = \theta_1 | X = x)$ . Let

$$h(x) = \pi f_{\theta_1}(x) + (1 - \pi)f_{\theta_2}(x)$$

Show that

$$\int \pi(x)h(x) dx = \pi$$

$$\int \pi(x)f_{\theta_1}(x) dx \geq \pi$$

6. Let  $Z$  be a real valued random variable with  $E(|Z|) < \infty$ . Let  $D$  be the real line and

$$L(z, d) = k_1(z - d) \quad \text{for } d \leq z$$

$$= k_2(d - z) \quad \text{for } d \geq z$$

where  $k_1$  and  $k_2$  are positive constants. Let  $d^*$  be a number which satisfies

$$P(Z \leq d^*) \geq \frac{k_1}{k_1 + k_2} \quad \text{and} \quad P(Z \geq d^*) \geq \frac{k_2}{k_1 + k_2}$$

Show that

$$E(L(Z, d^*)) = \inf_{-\infty < d < \infty} E(L(Z, d))$$

7. Let  $\Theta = \{\theta_1, \dots, \theta_n\}$  be a set of real numbers. Let  $g$  be a prior distribution on  $\Theta$ , that is  $g(\theta_i) \geq 0$  and  $\sum_{i=1}^n g(\theta_i) = 1$ . Let  $D$  be the real numbers. Let  $L(d, \theta) = W(|d - \theta|)$  where  $W$  is a non-negative function defined on  $[0, \infty]$ . Let  $\phi(d) = \sum_{i=1}^n W(|d - \theta_i|)g(\theta_i)$

i) Show that if  $W'$  and  $W''$  exist on  $[0, \infty)$ , with  $W'(0) = 0$ ,  $W''(0) = 0$  and  $W''(a) > 0$  for  $a > 0$  then  $\phi$  is minimized at the unique point  $d^*$  satisfying

$$\sum_{\theta_i > d^*} W'(\theta_i - d^*)g(\theta_i) = \sum_{\theta_i < d^*} W'(d^* - \theta_i)g(\theta_i)$$

ii) Suppose  $W'$  and  $W''$  exist on  $(0, \infty$  with  $W''(a) < 0$  for  $a > 0$  and that  $W$  is right continuous at zero. Show that  $\phi$  is minimized at a point  $d^*$  where  $d^* = \theta_i$  for some choice of  $i$ .