

# Stat 643 Mid Term Exam

## Fall 1996

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1. Consider a model  $\mathcal{P} = \{P_\theta\}$ , where  $\Theta = \{1, 2, 3\}$ ,  $\mathcal{X} = \{x_1, x_2, x_3, x_4\}$  and the distributions  $P_\theta$  are specified in the table below.

	$x_1$	$x_2$	$x_3$	$x_4$
$\theta = 1$	.6	.1	.2	.1
$\theta = 2$	.3	.1	.2	.4
$\theta = 3$	0	.2	.4	.4

a) Find a minimal sufficient statistic  $T : \mathcal{X} \rightarrow \mathcal{T}$ , where  $\mathcal{T}$  has 3 elements. Give the distribution of  $T$  in a tabular form similar to that used above for specifying the distribution of  $X$ .

Suppose that one is to make a decision about  $\theta$ , where  $\mathcal{A} = \Theta = \{1, 2, 3\}$  and  $L(\theta, a) = I[a \neq \theta]$ .

b) Consider the behavioral decision rule  $\phi$  defined by

$$\begin{aligned}
 \phi_{x_1}(\{1\}) &= .8 & \phi_{x_1}(\{2\}) &= .2 & \phi_{x_1}(\{3\}) &= 0 \\
 \phi_{x_2}(\{1\}) &= .6 & \phi_{x_2}(\{2\}) &= .3 & \phi_{x_2}(\{3\}) &= .1 \\
 \phi_{x_3}(\{1\}) &= .3 & \phi_{x_3}(\{2\}) &= .6 & \phi_{x_3}(\{3\}) &= .1 \\
 \phi_{x_4}(\{1\}) &= 0 & \phi_{x_4}(\{2\}) &= .2 & \phi_{x_4}(\{3\}) &= .8
 \end{aligned}$$

Find a rule that is a function of your sufficient statistic from a) and is risk equivalent to  $\phi$ .

c) Argue directly from the definition of admissibility that  $\delta_1(x) \doteq 1$  is admissible.

d) Show that

$$\delta_2(x) = \begin{cases} 1 & \text{if } x = x_1 \text{ or } x = x_2 \\ 3 & \text{if } x = x_3 \text{ or } x = x_4 \end{cases}$$

is Bayes versus a prior  $G$  that places mass  $\frac{2}{3}$  on  $\theta = 1$  and mass  $\frac{1}{3}$  on  $\theta = 3$ .

e) Show that  $\delta_2$  defined in d) is admissible.

f) Consider a randomized rule  $\psi$  in this decision problem defined by  $\psi(\{\delta_1\}) = \frac{1}{2}$  and  $\psi(\{\delta_2\}) = \frac{1}{2}$ . Find a behavioral decision rule  $\phi'$  that is risk equivalent to  $\psi$ .

2. Consider the family of distributions  $\mathcal{P} = \{P_\theta\}$  on  $\mathcal{X} = [0, \infty)$  indexed by the parameter  $\theta = (\theta_1, \theta_2) \in \Theta \subset \mathcal{R}^2$ , dominated by the  $\sigma$ -finite measure  $\mu = \Delta + \lambda$  for  $\Delta$  a unit point mass at 0 and  $\lambda$  Lebesgue measure on  $\mathcal{X}$ , where

$$f_\theta(x) = \frac{dP_\theta}{d\mu}(x) \propto \exp(\theta_1 I[x = 0] + \theta_2 x) \quad .$$

a) What are the natural parameter space and "normalizing constant"  $K(\theta)$  for this family of distributions?

b) Use  $K(\theta)$  to find the moment generating function for  $X \sim P_\theta$ ,  $E_\theta \exp sX$ .

c) Identify the UMVUE for  $\gamma(\theta) = P_\theta[X_1 = 0]$  based on  $X_1, X_2, \dots, X_n$  iid  $P_\theta$  for  $\theta$  in the natural parameter space. Argue very carefully that your estimator is UMVU.

3. Consider squared error loss estimation of the binomial parameter " $p$ ."

a) Write out (and to the extent possible simplify) the risk function for a linear estimator of  $p$ ,  $\delta'(x) = Ax + B$ .

Using the result from a) it is possible to show that  $\delta(x) = \frac{x + \frac{\sqrt{n}}{2}}{n + \sqrt{n}}$  has constant risk. (Don't bother to show this here.) It is also the case that if conditional on  $p$ ,  $X \sim \text{Binomial}(n, p)$  and  $p \sim \text{Beta}(\alpha, \beta)$ ,  $E[p|X = x] = \frac{\alpha + x}{\alpha + \beta + n}$ . (Again, you need not show this here.)

b) Argue carefully that  $\delta$  is an admissible estimator of  $p$ .

c) Take the result in b) as given and prove that  $\delta$  is the **unique** minimax rule for this estimation problem.