

# STAT215: Homework 2

Due: Wednesday, Feb 14

1. (10 pt) Suppose we take one observation,  $X$ , from the discrete distribution,

$$\Pr(X = x|\theta) \begin{array}{cccccc} x & -2 & -1 & 0 & 1 & 2 \\ (1 - \theta)/4 & \theta/12 & 1/2 & (3 - \theta)/12 & \theta/4, & 0 \leq \theta \leq 1 \end{array}$$

Find a real-valued statistic  $T(X)$  with  $\mathbb{E}[T(X)] \equiv \theta$  ( $T$  is an unbiased estimator of  $\theta$ , but might take values outside  $[0, 1]$ ). Obtain the maximum likelihood estimator (MLE)  $\hat{\theta}(x)$  of  $\theta$  and show that it is not unique. Is any choice of MLE unbiased?

2. (10 pt) Bickel & Doksum pg 153, problem 2.3.8. Nine points (out of 10) for a correct solution in  $p = 1$  dimensions. Hint: In  $p = 1$  dimension,  $|x - y|^\alpha = [(x - y)^2]^\alpha$ ; in  $\mathbb{R}^p$ ,  $|x - y|^\alpha = [\sum_{j=1}^p (x_j - y_j)^2]^\alpha$ .
3. (10 pt) Let  $(X_1, \dots, X_n)$  be a random sample from the uniform distribution on the interval  $(\theta - \frac{1}{2}, \theta + \frac{1}{2})$ , where  $\theta \in \mathbb{R}$  is unknown. Let  $X_{(j)}$  be the  $j^{\text{th}}$  order statistic.
- (a) Show that  $(X_{(1)} + X_{(n)})/2$  is strongly consistent for  $\theta$ , *i.e.*, that  $\lim_{n \rightarrow \infty} (X_{(1)} + X_{(n)})/2 = \theta$  a.s.
- (b) Show that  $\bar{X}_n := (X_{(1)} + \dots + X_{(n)})/n$  is  $L^2$  consistent.

4. (10 pt) Let  $\{X_i\} \stackrel{\text{iid}}{\sim} \text{No}(\mu, \sigma^2)$  be a random sample from the normal distribution with unknown mean  $\mu \in \mathbb{R}$  and known variance  $\sigma^2 > 0$ . For fixed  $t \neq 0$ , find the MLE  $T_n(X)$  of  $e^{t\mu}$  and find a constant  $c_n$  for which  $S_n(X) := c_n T_n(X)$  is an unbiased estimator of  $e^{t\mu}$ . Show that the variance of  $S_n$  is larger than the Information Inequality lower bound, but that the ratio of its variance to the lower bound converges to 1 as  $n \rightarrow \infty$ . Recall that MLE's in different parametrizations  $\eta = g(\theta)$  are related simply by  $\hat{\eta} = g(\hat{\theta})$  for any smooth function  $g$ , like  $g(x) = e^{tx}$ .

5. (10 pt) Let  $X$  have density function  $f(x|\theta)$ ,  $x \in \mathbb{R}^d$ , and let  $\theta$  have (proper) prior density  $\pi(\theta)$ . Let  $\delta^\pi(x)$  denote the Bayes estimate of  $\theta$  under  $\pi(\theta)$  for squared-error loss (*i.e.*,  $\delta^\pi(x) := \mathbb{E}[\theta | X = x]$ ) and suppose  $\delta^\pi$  has finite Bayes risk  $r(\pi, \delta^\pi) = \mathbb{E}[|\delta^\pi(X) - \theta|^2]$ . Show that for any other estimator  $\delta(x)$ ,

$$r(\pi, \delta) - r(\pi, \delta^\pi) = \int (\delta(x) - \delta^\pi(x))^2 f(x) dx$$

where  $f(x)$  is the marginal density of  $X$ . If  $f(x|\theta)$  is normal  $\text{No}(\theta, 1)$ , consider the collection of estimators of the form  $\delta(X) := cX + d$ . Show that whenever  $0 \leq c < 1$

these estimators are all proper Bayes estimators, and hence admissible [Hint: Find a prior  $\pi$  for which  $\delta^\pi(X) = cX + d$ ]. Show that if  $c > 1$  the resulting estimator is inadmissible.

6. (10 pt) Bickel & Doksum pg 197, problem 3.2.1
7. (10 pt) Bickel & Doksum pg 197, problem 3.2.4