

## Statistics 582, Problem Set 6

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**Due:** Wednesday, February 17, 2010.

**Reminder:** Midterm exam, Friday February 12.

**Reading:** Chapter 5, sections 7-8.

- (a) Suppose that  $X \sim F$  on  $\mathbb{R}$ . Let  $\rho_p(x) \equiv x(p - 1_{(-\infty, 0]}(x))$  for  $p \in (0, 1)$  and  $x \in \mathbb{R}$ . Show that  $h_p(t) \equiv E_F \rho_p(X - t)$  is minimized by  $F^{-1}(p)$ . (Note that  $\rho_{1/2}(x) = |x|/2$ , so  $h_{1/2}(t)$  is minimized by any median of  $F$  as we already know.)  
(b) Suppose that  $(X|\boldsymbol{\theta} = \theta) \sim P_\theta$  on  $\mathbb{R}$  and that  $\boldsymbol{\theta} \sim \Lambda$ . Fix  $p \in (0, 1)$ , and let  $L(\theta, a) \equiv \rho_p(\theta - a)$ . Show that the Bayes rule with respect to the prior  $\Lambda$  for this loss function is the  $p$ -th quantile of the posterior distribution  $\Lambda(\theta|X)$ .
- Let  $\mathcal{X} = \{0, 1\}$ ,  $\mathcal{A} = \Theta = \{1, 2\}$ , and assume that the losses are given by  $L(1, 1) = L(2, 2) = 0$ ,  $L(1, 2) = a$ ,  $L(2, 1) = b$ . Suppose that the statistician can observe either  $X$  or  $Y$  where

$$\begin{aligned} p_1(1) &= P_1(X = 1) = 2/3, & p_2(1) &= P_2(X = 1) = 1/2, \\ p_1^*(1) &= P_1(Y = 1) = 3/4, & p_2^*(1) &= P_2(Y = 1) = 1/2. \end{aligned}$$

Let  $\underline{\lambda} = (\lambda, 1 - \lambda)$ ,  $\lambda \in [0, 1]$  be the prior distribution over  $\Theta$ .

- Find the Bayes risk when  $X$  is observed, and similarly for  $Y$ .
  - In the case  $a = b$ ,  $\lambda = 1/2$ , would the statistician prefer to observe  $X$  or  $Y$ ?
  - For general  $a \neq b$ ,  $\lambda \in (0, 1)$  would the statistician prefer to observe  $X$  or  $Y$ ?
- Consider Example 5.5.4 on pages 16 and 17 of the Chapter 5 notes.
    - Show that the variance of  $\hat{\psi}$  is given by

$$\text{Var}(\hat{\psi}_n) = \frac{1}{n} \left\{ \frac{1}{B} \sum_{j=1}^B \frac{\theta_j}{\xi_j} - \psi(\theta)^2 \right\}.$$

[Hint: use the formula  $\text{Var}(Y) = E\text{Var}(Y|X) + \text{Var}[E(Y|X)]$  twice.]

- Use the result of (a) to show that

$$\text{Var}(\hat{\psi}_n) \leq \frac{1}{n\delta}$$

under the assumption that  $\xi_j \geq \delta > 0$  for all  $1 \leq j \leq B$ .

4. **Optional bonus problem 1:** (Compare with Lehmann and Casella, TPE, Examples 5.1 and 5.2, pages 254-255.)
- Let  $(X|\sigma^2) \sim N(0, \sigma^2)$ . Show that the conjugate prior for  $\sigma^2$  is the distribution of  $1/Y$  where  $Y$  has a gamma distribution.
  - Suppose that  $(X|\theta, \kappa) \sim N(\theta, 1/\kappa)$ ,  $(\theta|\kappa) \sim N(\mu, \tau/\kappa)$ , and  $\kappa \sim \text{Gamma}(\alpha, \beta)$ . Show that the posterior distribution of  $(\theta, \kappa)$  has the same form as the prior.
  - Find the marginal posterior distribution for  $\theta$  in (b).
  - If  $X_1, \dots, X_n$  are i.i.d. as  $X$  in (b), find the limiting distribution of the Bayes estimator of  $\theta$  for squared-error loss.
5. **Optional bonus problem 2:** Suppose that  $X \sim P_\theta$  for  $\theta \in \Theta \subset R^k$  has well-defined Fisher information matrix  $I(\theta)$  for  $\theta$ . The *Jeffreys prior* distribution  $\Lambda_J$  has density  $\lambda_J(\theta) = \det(I(\theta))^{1/2}$  with respect to Lebesgue measure on  $\Theta$ . Note that  $\Lambda_J$  may not be a finite measure, and even if  $\Lambda_J$  is a finite measure, it may not have total mass 1. If a prior distribution is a finite measure, then call it a *proper prior distribution*, and correspondingly if it is not a finite measure, call it an *improper prior distribution*. If the resulting posterior distribution is a finite measure, call it a *proper posterior distribution*, and (by convention) normalize it to have total mass 1. See Lehmann and Casella, TPE, pages 230, 234, 287, 305.
- Suppose that  $X \sim \text{Bernoulli}(\theta)$ . Find the Jeffrey's prior density  $\lambda_J$  for  $\theta$ . Is  $\Lambda_J$  a finite measure? If it is finite, what is  $\Lambda_J((0, 1))$ ? Find the corresponding posterior distribution of  $\Theta$  starting with the Jeffrey's prior.
  - Suppose that  $X \sim \text{Poisson}(\theta)$  with  $\theta \in (0, \infty)$ . Find the Jeffrey's prior density  $\lambda_J$  for  $\theta$ . Is  $\Lambda_J$  a finite measure? If it is finite, what is  $\Lambda_J((0, \infty))$ ? Find the corresponding posterior distribution of  $\Theta$  starting with the Jeffrey's prior. Is it ever a proper posterior distribution?
  - Suppose that  $X \sim \text{Geometric}(\theta)$ , i.e. the number of trials until the first success in i.i.d. Bernoulli trials with probability  $\theta$  of success for each trial – recall Chapter 1, section 1. Find the Jeffrey's prior density  $\lambda_J$  for  $\theta$ . Is  $\Lambda_J$  a finite measure? If it is finite, what is  $\Lambda_J((0, 1))$ ? Find the corresponding posterior distribution of  $\Theta$  starting with the Jeffrey's prior. If we observe  $X_1, \dots, X_n$  i.i.d.  $\text{Geometric}(\theta)$ , so that  $\sum X_i \sim \text{Negative Binomial}(n, \theta)$  is the posterior distribution “proper” for some  $n$ ?
  - Suppose that  $X \sim \text{Weibull}(\theta)$  with  $\theta = (\alpha, \beta) \in (0, \infty) \times (0, \infty)$  as in chapters 3 and 4. Find the Jeffrey's prior density  $\lambda_J$  for  $\theta$ . Is  $\Lambda_J$  a finite measure? If it is finite, what is  $\Lambda_J((0, \infty)^2)$ ? Find the corresponding posterior distribution of  $\Theta$  starting with the Jeffrey's prior.