

### Stat 461-561: Quiz 3 Solutions

Friday 16th March 2007

**Exercise 1.** Suppose that  $x_{1:n} = (x_1, \dots, x_n)$  is a random sample from a Poisson distribution with unknown mean  $\theta$ . Two models for the prior distribution of  $\theta$  are contemplated:

$$\begin{aligned} H_0 &: \pi_0(\theta) = \exp(-\theta) 1_{(0,\infty)}(\theta), \\ H_1 &: \pi_1(\theta) = \theta \exp(-\theta) 1_{(0,\infty)}(\theta). \end{aligned}$$

(a) Calculate the posterior mean  $\mathbb{E}[\theta | x_{1:n}]$  under both models.

We have

$$\begin{aligned} f(x_{1:n} | \theta) &= \prod_{i=1}^n \exp(-\theta) \frac{\theta^{x_i}}{x_i!} \\ &= \exp(-n\theta) \theta^{S_n} \end{aligned}$$

where  $S_n = \sum_{i=1}^n x_i$ . So

$$\begin{aligned} \pi_0(\theta | x_{1:n}) &\propto \exp(-\theta) \exp(-n\theta) \theta^{S_n} \\ &\propto \exp(-(n+1)\theta) \theta^{S_n}. \end{aligned}$$

So  $\pi_0(\theta | x_{1:n}) = \text{Gamma}(\theta; S_n + 1, n + 1)$  and

$$\mathbb{E}[\theta | x_{1:n}] = \frac{S_n + 1}{n + 1}.$$

We also have

$$\begin{aligned} \pi_1(\theta | x_{1:n}) &\propto \theta \exp(-\theta) \exp(-n\theta) \theta^{S_n} \\ &\propto \exp(-(n+1)\theta) \theta^{S_n+1} \end{aligned}$$

so  $\pi_1(\theta | x_{1:n}) = \text{Gamma}(\theta; S_n + 2, n + 1)$  and

$$\mathbb{E}[\theta | x_{1:n}] = \frac{S_n + 2}{n + 1}.$$

The first model puts more mass on smaller values of  $\theta$  so the posterior distribution  $\pi_0(\theta | x_{1:n})$  is shifted to the left of  $\pi_1(\theta | x_{1:n})$ .

(b) Calculate the Bayes factor

$$B_{01} = \frac{\pi(x_{1:n} | H_0)}{\pi(x_{1:n} | H_1)}.$$

The Bayes factor is given by

$$\begin{aligned}
 B_{01} &= \frac{\int \exp(-(n+1)\theta) \theta^{S_n} d\theta}{\int \exp(-(n+1)\theta) \theta^{S_n+1} d\theta} \\
 &= \frac{\Gamma(S_n+1) / ((n+1)^{S_n+1})}{\Gamma(S_n+2) / ((n+1)^{S_n+2})} \\
 &= \frac{n+1}{S_n+1}.
 \end{aligned}$$

(c) Assuming that  $\pi(H_0) = \pi(H_1) = \frac{1}{2}$ , compute the posterior probabilities  $\pi(H_0|x_{1:n})$  and  $\pi(H_1|x_{1:n})$ .

We have

$$\begin{aligned}
 \pi(H_0|x_{1:n}) &= 1 - \pi(H_1|x_{1:n}) \\
 &= \frac{\pi(x_{1:n}|H_0)\pi(H_0)}{\pi(x_{1:n}|H_0)\pi(H_0) + \pi(x_{1:n}|H_1)\pi(H_1)} \\
 &= \frac{\pi(x_{1:n}|H_0)}{\pi(x_{1:n}|H_0) + \pi(x_{1:n}|H_1)} \\
 &= \frac{1}{1 + B_{01}^{-1}} = \frac{1}{1 + \frac{S_n+1}{n+1}} \\
 &= \frac{n+1}{S_n + n + 2}.
 \end{aligned}$$

**Exercise 2.** Let  $\theta$  be a real-valued parameter and let  $f(x|\theta)$  be the probability density function of an observation  $x$  given  $\theta$ . The prior distribution is of the form

$$\pi(\theta) = \beta \delta_{\theta_0}(\theta) + (1 - \beta) g(\theta)$$

where  $g(\theta)$  is a standard probability density function.

(a) Derive an expression for  $\pi(\theta_0|x)$ , the posterior probability of  $H_0 : \theta = \theta_0$ .

We have

$$\pi(\theta_0|x) = \frac{\beta f(x|\theta_0)}{\beta f(x|\theta_0) + (1 - \beta) m(x)}$$

where

$$m(x) = \int f(x|\theta) m(\theta) d\theta.$$

(b) Derive the Bayes factor for the null hypothesis  $H_0$  against the alternative  $H_1 : \theta \sim g(\theta)$ , that is

$$B(x) = \frac{\pi(x|H_0)}{\pi(x|H_1)}.$$

The Bayes factor is

$$B(x) = \frac{f(x|\theta_0)}{m(x)}.$$

(c) Express  $\pi(\theta_0|x)$  in terms of  $B(x)$ .

We have

$$\pi(\theta_0|x) = \left(1 + \frac{1-\beta}{\beta B(x)}\right)^{-1}.$$

(d) Explain how you would use  $B(x)$  to construct a most powerful test of size  $\alpha$  for  $H_0$ , against the alternative  $H_1$ . [Hint: Apply Neyman-Pearson to test hypothesis on the distribution of  $X$ ].

The simple hypothesis  $\theta = \theta_0$  can be tested against the simple hypothesis that the density of  $x$  is  $m(x)$ ; i.e.  $H_0: X \sim f(x|\theta_0)$  and  $H_1: X \sim m(x)$ . The Neyman-Pearson lemma says that the most powerful test of size  $\alpha$  rejects  $H_0$  when  $B(x) = \frac{f(x|\theta_0)}{m(x)} < C_\alpha$ , where  $C_\alpha$  is chosen such that

$$\int_{\{x: B(x) < C_\alpha\}} f(x|\theta_0) dx = \alpha.$$

Suppose that  $X_1, \dots, X_n$  are i.i.d. with  $X_i \sim \mathcal{N}(\theta, v)$ . Let  $H_0: \theta = 0$ , let  $\beta = \frac{1}{2}$  and let

$$g(\theta) = \mathcal{N}(\theta; 0, w).$$

Show that if the sample mean  $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$  is observed to be  $10(v/n)^{1/2}$ , then

(f) the posterior probability of  $H_0$  converges to 1, as  $n \rightarrow \infty$ .

The Bayes factor is given by

$$\frac{\frac{1}{\sqrt{\frac{v}{n}}} \exp\left(-\frac{10^2 \frac{v}{n}}{2 \frac{v}{n}}\right)}{\frac{1}{\sqrt{\frac{v}{n} + w}} \exp\left(-\frac{10^2 \frac{v}{n}}{2(\frac{v}{n} + w)}\right)} \rightarrow \infty \text{ as } n \rightarrow \infty.$$

(e) the most powerful test of size  $\alpha = 0.05$  will reject  $H_0$  for any value of  $n$  [Hint: Apply Neyman-Pearson to test hypothesis on the distribution of  $\bar{X}$ ]

We now have  $x = (x_1, \dots, x_n)$ . The statistic  $\bar{x}$  is sufficient. Under  $H_0$ ,  $\bar{x} \sim \mathcal{N}(0, \frac{v}{n})$  and under  $H_1$ ,  $\bar{x} \sim \mathcal{N}(0, \frac{v}{n} + w)$ . So Neyman-Pearson rejects when

$$|\bar{x}| > c$$

where  $c$  is selected as

$$\begin{aligned} & \int_{\{\bar{x}: |\bar{x}| > c\}} \mathcal{N}\left(\bar{x}; 0, \frac{v}{n}\right) d\bar{x} \\ &= \int_{\{u: |u| > c\sqrt{\frac{n}{v}}\}} \mathcal{N}(u; 0, 1) du. \\ &= \alpha \end{aligned}$$

so we have  $c\sqrt{\frac{n}{v}} = z_{\alpha/2}$  and

$$|\bar{x}| \sqrt{\frac{n}{v}} > z_{\alpha/2}.$$

For  $\bar{x} = 10(v/n)^{1/2}$ , we have

$$|\bar{x}| \sqrt{\frac{n}{v}} = 10 > z_{0.05/2}$$

so  $H_0$  is rejected.

**Exercise 3.** Consider  $x = (x_1, x_2)$  with the following distribution

$$f(x_1, x_2 | \theta) \propto \int_0^\infty t^{2n-1} \exp\left(-\frac{1}{2}\left(t^2 + n(x_1 t - \zeta)^2 + n(x_2 t - \xi)^2\right)\right) dt$$

with  $\theta = (\zeta, \xi) \in \mathbb{R} \times \mathbb{R}$ . The prior distribution is improper

$$\pi(\theta) \propto 1.$$

(a) Show that  $\pi(\zeta | x) = \pi(\zeta | x_1)$  and that  $f(x_1 | \theta) = f(x_1 | \zeta)$  but that  $\pi(\zeta | x_1)$  is not proportional to  $f(x_1 | \zeta)$ .

We have

$$\begin{aligned} \pi(\zeta | x) &\propto \int \int_0^\infty t^{2n-1} \exp\left(-\frac{1}{2}\left(t^2 + n(x_1 t - \zeta)^2 + n(x_2 t - \xi)^2\right)\right) dt d\xi \\ &\propto \int_0^\infty t^{2n-1} \exp\left(-\frac{1}{2}\left(t^2 + n(x_1 t - \zeta)^2\right)\right) dt \end{aligned}$$

so  $\pi(\zeta | x)$  is only a function of  $x_1$ . We also have

$$\begin{aligned} f(x_1 | \theta) &= \int f(x_1, x_2 | \theta) dx_2 \\ &\propto \int \int_0^\infty t^{2n-1} \exp\left(-\frac{1}{2}\left(t^2 + n(x_1 t - \zeta)^2 + nt^2\left(x_2 - \frac{\xi}{t}\right)^2\right)\right) dt dx_2 \\ &\propto \int_0^\infty t^{2n-2} \exp\left(-\frac{1}{2}\left(t^2 + n(x_1 t - \zeta)^2\right)\right) dt \end{aligned}$$

so  $f(x_1 | \theta)$  is only a function of  $\zeta$ . However,  $\pi(\zeta | x)$  is not proportional to  $f(x_1 | \theta)$ .

**Hints.**

- The Poisson distribution of parameter  $\theta$  is a distribution on the set of integers  $0, 1, 2, \dots$  such that  $f(x | \theta) = \exp(-\theta) \frac{\theta^x}{x!}$  and we have  $\mathbb{E}[X] = \theta$ .
- The Gamma distribution  $\text{Gamma}(a, b)$  admits for density

$$\frac{b^a}{\Gamma(a)} x^{a-1} \exp(-bx) 1_{(0, \infty)}(x)$$

and mean  $\mathbb{E}[X] = \frac{a}{b}$ .

- For integers  $n \geq 1$ , we have  $\Gamma(n) = (n-1)!$