

Ma 494 — Theoretical Statistics

Solutions for Problem Set #5 — Due March 24, 2010

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NOTE: 5 problems on 4 pages.

1. (i) $\hat{p} = M/N = 0.94$ for $N = 1000$ simulated samples of size n . By Theorem 5.3.1 on page 369 of the text (with $X = M$ and $n = N$), a symmetric 95% confidence interval for the true coverage probability p is

$$\begin{aligned} \left(\hat{p} - 1.960 \sqrt{\frac{\hat{p}(1-\hat{p})}{1000}}, \hat{p} + 1.960 \sqrt{\frac{\hat{p}(1-\hat{p})}{1000}} \right) &= (0.94 - 0.015, 0.94 + 0.015) \\ &= (0.925, 0.955) \end{aligned}$$

This contains $p = 0.95$, so that $M/N = 0.94$ is consistent with $p = 0.95$.

(ii) If $N = 1000$ is replaced by $N = 10,000$, the confidence interval is

$$\begin{aligned} \left(\hat{p} - 1.960 \sqrt{\frac{\hat{p}(1-\hat{p})}{10,000}}, \hat{p} + 1.960 \sqrt{\frac{\hat{p}(1-\hat{p})}{10,000}} \right) &= (0.94 - 0.005, 0.94 + 0.005) \\ &= (0.935, 0.945) \end{aligned}$$

This DOES NOT contain $p = 0.95$, so that $M/N = 0.94$ is NOT consistent with $p = 0.95$.

2. Since Y has a gamma distribution with parameters (r, θ) (see Definition 4.6.2 on page 329 in the text), the density of Y given θ is

$$f_Y(y, \theta) = \frac{\theta^r}{\Gamma(r)} y^{r-1} e^{-\theta y}$$

Note that r is assumed fixed. The prior distribution on θ is gamma with parameters (s, μ) , so that the prior density (for θ) is

$$\pi_0(\theta) = \frac{\mu^s}{\Gamma(s)} \theta^{s-1} e^{-\mu \theta}$$

Thus the Bayesian joint probability density of (θ, y) is

$$\begin{aligned} f_{\Theta, Y}(\theta, y) &= \pi_0(\theta) f_Y(y, \theta) = \frac{\mu^s}{\Gamma(s)} \theta^{s-1} e^{-\mu \theta} \frac{\theta^r}{\Gamma(r)} y^{r-1} e^{-\theta y} \\ &= \frac{\mu^s y^{r-1}}{\Gamma(s) \Gamma(r)} \theta^{r+s-1} e^{-\theta(\mu+y)} = C(y) \theta^{r+s-1} e^{-\theta(\mu+y)} \end{aligned} \quad (1)$$

(i) By definition, the Bayesian posterior distribution given $y = Y$ is the two-dimensional density in (1) conditional on $y = Y$. By Definition 3.11.1 page 250 in the text, this conditional density is of the same form

$$\pi_1(\theta | Y) = f_{\Theta|Y}(\theta | Y) = C_1(Y) \theta^{r+s-1} e^{-\theta(\mu+Y)} \tag{2}$$

where $\int \pi_1(\theta | Y) d\theta = 1$. The form of (2) as a function of θ indicates that $\pi_1(\theta | Y)$ is a gamma density with parameters $(r + s, \mu + Y)$ (see Definition 4.6.2 page 329). Since $\int \pi_1(\theta | Y) d\theta = 1$, it follows that $C_1(Y) = (\mu + Y)^{r+s} / \Gamma(r + s)$.

(ii) By Theorem 5.8.1 page 420 in the text, the Bayes estimator $\hat{\theta}_B$ of θ for one observation Y with square-loss risk is the same as the mean of the posterior density $\pi(\theta | Y)$. By Theorem 4.6.3 page 330 in the text, if W has a gamma distribution with parameters (t, λ) then $E(W) = t/\lambda$ and $\text{Var}(W) = t/\lambda^2$. By (2), the distribution of Θ given Y is gamma with parameters $(r + s, \mu + Y)$. Thus $\hat{\theta}_B = \int \theta \pi_1(\theta | Y) d\theta = E(\Theta | Y) = t/\lambda = (r + s)/(\mu + Y)$.

3. (i) The likelihood is

$$L(p, Y_1, \dots, Y_n) = \prod_{j=1}^n (1 - p)^{Y_j - 1} p = (1 - p)^{\sum_{j=1}^n (Y_j - 1)} p^n$$

Thus if $Y = (Y_1, \dots, Y_n)$

$$\begin{aligned} \log L(p, Y) &= \left(\left(\sum_{j=1}^n Y_j \right) - n \right) \log(1 - p) + n \log(p) \\ \frac{\partial}{\partial p} \log L(p, Y) &= \frac{n}{p} - \frac{\left(\sum_{j=1}^n Y_j \right) - n}{1 - p} \end{aligned} \tag{3}$$

Setting the expression in (3) equal to zero leads to

$$p \left(\left(\sum_{j=1}^n Y_j \right) - n \right) = n(1 - p) = p \left(\sum_{j=1}^n Y_j \right) - np = n - np$$

Thus the maximum likelihood estimator is

$$\hat{p} = \frac{n}{\sum_{j=1}^n Y_j} = \frac{1}{\bar{Y}} \tag{4}$$

where $\bar{Y} = (1/n) \sum_{j=1}^n Y_j$. Since $Y_j \geq 1$ for all j , $\bar{Y} \geq 1$ and $0 \leq \hat{p} \leq 1$, as expected.

(ii) Since $f(y, p) = (1 - p)^{y-1}p$ for one observation, it follows from (3) with $n = 1$ that

$$\frac{\partial}{\partial p} \log f(Y, p) = \frac{1}{p} - \frac{Y - 1}{1 - p}, \quad -\frac{\partial^2}{\partial p^2} \log f(Y, p) = \frac{1}{p^2} + \frac{Y - 1}{(1 - p)^2} \quad (5)$$

By Theorem 4.4.1 on page 318 of the text, $E(Y) = 1/p$. (This also follows from (5) and $E((\partial/\partial p) \log f(Y, p)) = 0$.) Thus by (5), the Fisher information is

$$\begin{aligned} I(f, p) &= -E \left(\frac{\partial^2}{\partial p^2} \log f(Y, p) \right) = \frac{1}{p^2} + \frac{E(Y) - 1}{(1 - p)^2} \\ &= \frac{1}{p^2} + \frac{1 - p}{p(1 - p)^2} = \frac{1}{p} \left(\frac{1}{p} + \frac{1}{1 - p} \right) = \frac{1}{p^2(1 - p)} \end{aligned} \quad (6)$$

By equation (5.6) in the Math 494 notes,

$$\left(\hat{p} - \frac{1.96}{\sqrt{nI(f, \hat{p})}}, \hat{p} + \frac{1.96}{\sqrt{nI(f, \hat{p})}} \right)$$

is an asymptotic central 95% confidence interval for p . By (4) and (6), $\hat{p} = 1/\bar{Y}$ and

$$\frac{1}{nI(f, \hat{p})} = \frac{\hat{p}^2(1 - \hat{p})}{n} = \frac{\bar{Y} - 1}{n\bar{Y}^3}$$

By assumption, $\bar{Y} = 3$ and $n = 100$. Thus the asymptotic 95% confidence interval for p is

$$\left(\frac{1}{\bar{Y}} - 1.960\sqrt{\frac{\bar{Y} - 1}{n\bar{Y}^3}}, \frac{1}{\bar{Y}} + 1.960\sqrt{\frac{\bar{Y} - 1}{n\bar{Y}^3}} \right) = (0.2800, 0.3866)$$

4. Under hypothesis H_0 , the Y_i are normally distributed $N(95, 15^2)$ so that \bar{Y} is $N(95, 15^2/22)$. If λ satisfies $\alpha = P(\bar{Y} \geq \lambda) = 0.06$, then

$$P \left(\frac{\bar{Y} - 95}{\sqrt{15^2/22}} \geq \frac{\lambda - 95}{\sqrt{15^2/22}} \right) = P \left(Z \geq \frac{\lambda - 95}{\sqrt{15^2/22}} \right) = 0.06$$

where Z is standard normal ($N(0, 1)$). This implies $(\lambda - 95)/\sqrt{15^2/22} = 1.555$ by Table A.1 and

$$\lambda = 1.555\sqrt{\frac{15^2}{22}} + 95 = 99.97$$

Thus, values of $\bar{Y} > 99.97$ cause H_0 to be rejected using the standard one-sided test at level of significance $\alpha = 0.06$.

5. (i) Here

$$\begin{aligned} \alpha &= P(X \geq 0.90 \mid H_0) = \int_{0.90}^1 f(x, 1) dx = \int_{0.90}^1 2x dx \\ &= x^2 \Big|_{x=0.90}^{x=1} = 1 - 0.90^2 = 1 - 0.81 = 0.19 \end{aligned}$$

(ii) If $H_1 : \theta = 10$, the power is

$$\begin{aligned} \text{Pow} &= P(X \geq 0.90 \mid H_1) = \int_{0.90}^1 f(x, 10) dx = \int_{0.90}^1 10x^{11} dx \\ &= x^{12} \Big|_{x=0.90}^{x=1} = 1 - 0.90^{12} = 1 - 0.314 = 0.686 \end{aligned}$$

and $\beta = 1 - \text{Pow} = 1 - 0.686 = 0.314$.