

Homework#2 Statistical Inference II

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Problem 2.1

Referring to Example 1.5, suppose that X has the binomial distribution $\text{Bin}(n, p)$ and the family of prior distribution for p is the family of beta distribution $\text{Beta}(a, b)$.

(a) Show that the marginal distribution of X is the *beta-binomial* distribution with mass function

$$\binom{n}{x} \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \frac{\Gamma(x+a)\Gamma(n-x+b)}{\Gamma(n+a+b)}.$$

Solution:

The density function of $X | p \sim \text{Bin}(n, p)$ and $p \sim \text{Beta}(a, b)$ are

$$f(x|p) = \binom{n}{x} p^x (1-p)^{n-x}, \quad x = 0, 1, \dots, n$$

and

$$\pi(p) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} p^{a-1} (1-p)^{b-1}, \quad 0 < p < 1.$$

Therefore, the joint density function is

$$\begin{aligned} f(x, p) &= \binom{n}{x} p^x (1-p)^{n-x} \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} p^{a-1} (1-p)^{b-1} \\ &= \binom{n}{x} \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} p^{x+a-1} (1-p)^{n-x+b-1}. \end{aligned}$$

Then we obtain the marginal distribution of X by integrating the joint density function

$$\begin{aligned} f(x) &= \int_0^1 f(x, p) dp = \binom{n}{x} \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \int_0^1 p^{x+a-1} (1-p)^{n-x+b-1} dp \\ &= \binom{n}{x} \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \frac{\Gamma(x+a)\Gamma(n-x+b)}{\Gamma(n+a+b)}. \end{aligned}$$

(b) Show that the mean and the variance of the beta-binomial is given by

$$E(X) = \frac{na}{a+b} \quad \text{and} \quad \text{var}(X) = n \left(\frac{a}{a+b} \right) \left(\frac{b}{a+b} \right) \left(\frac{a+b+n}{a+b+1} \right).$$

Solution:

It is easy to obtain

$$E(X) = E\{E(X|p)\} = E(np) = nE(p) = \frac{na}{a+b}.$$

Similarly,

$$\begin{aligned} \text{var}(X) &= \text{var}\{E(X|p)\} + E\{\text{var}(X|p)\} \\ &= \text{var}(np) + E\{np(1-p)\} = n^2 \text{var}(p) + nE\{p(1-p)\} \\ &= n^2 \frac{ab}{(a+b)^2(a+b+1)} + n \int_0^1 \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} p^a (1-p)^b dp \\ &= n^2 \frac{ab}{(a+b)^2(a+b+1)} + n \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \frac{\Gamma(a+1)\Gamma(b+1)}{\Gamma(a+b+2)} \\ &= n^2 \frac{ab}{(a+b)^2(a+b+1)} + n \frac{ab}{(a+b)(a+b+1)} \\ &= n \left(\frac{a}{a+b} \right) \left(\frac{b}{a+b} \right) \left(\frac{a+b+n}{a+b+1} \right). \end{aligned}$$

Problem 3.1 [p.285]

For the situation of Example 3.1:

- (a) Verify the Bayes estimator will only depend on the data through $Y = \max_i X_i$.

Solution:

According to Example 3.1, we have

$$X_i | \theta \sim U(0, \theta), \quad 0 \leq x_i \leq \theta \quad \text{for } i = 1, 2, \dots, n$$

and

$$1/\theta \sim \text{Gamma}(a, b), \quad 1/\theta > 0, \quad \text{where } a, b \text{ are known.}$$

Therefore, the joint density of X is

$$\begin{aligned} f(x_1, x_2, \dots, x_n | \theta) &= \prod_{i=1}^n f(x_i | \theta) = \prod_{i=1}^n \frac{1}{\theta} I(0 \leq x_i \leq \theta) \\ &= \frac{1}{\theta^n} I(0 \leq x_1, x_2, \dots, x_n \leq \theta) \\ &= \frac{1}{\theta^n} I(\max_i x_i \leq \theta \leq \infty) = \frac{1}{\theta^n} I(y \leq \theta \leq \infty). \end{aligned}$$

Here we define $z = 1/\theta$ and make a transformation

$$\theta = \frac{1}{z} \Rightarrow z = \frac{1}{\theta} \Rightarrow \left| \frac{dz}{d\theta} \right| = \theta^{-2}.$$

Then the density function of θ is

$$\pi_\theta(\theta | a, b) = \pi_z(1/\theta | a, b) \theta^{-2} = \frac{1}{\Gamma(a) b^a \theta^{a+1}} e^{-\frac{1}{b\theta}}.$$

This is the density function of inverse gamma distribution.

Now we can derive the posterior distribution

$$\begin{aligned}\pi_{\theta}(\theta | x) &\propto \frac{1}{\theta^{a+1}} e^{-\frac{1}{b\theta}} \frac{1}{\theta^n} I(y \leq \theta \leq \infty) \\ &\propto \frac{1}{\theta^{n+a+1}} e^{-\frac{1}{b\theta}} I(y \leq \theta \leq \infty).\end{aligned}$$

Therefore, the Bayes estimator is

$$\delta_{\lambda} = E\{\pi_{\theta}(\theta | x, a, b)\} = \frac{\int_0^{\infty} \theta \frac{1}{\theta^{n+a+1}} e^{-\frac{1}{b\theta}} I(y \leq \theta \leq \infty) d\theta}{\int_0^{\infty} \frac{1}{\theta^{n+a+1}} e^{-\frac{1}{b\theta}} I(y \leq \theta \leq \infty) d\theta} = \frac{\int_y^{\infty} \frac{1}{\theta^{n+a}} e^{-\frac{1}{b\theta}} d\theta}{\int_y^{\infty} \frac{1}{\theta^{n+a+1}} e^{-\frac{1}{b\theta}} d\theta}.$$

Hence the Bayes estimator is only depend on $Y = \max_i X_i$.

(b) Show that $E\{\pi_{\theta}(\theta | x, a, b)\}$ can be expressed as

$$E\{\pi_{\theta}(\theta | x, a, b)\} = \frac{1}{b(n+a-1)} \frac{\Pr(\chi_{2(n+a-1)}^2 < 2/by)}{\Pr(\chi_{2(n+a)}^2 < 2/by)},$$

where χ_{ν}^2 is a chi-squared random variable with ν degrees of freedom. (In this form, the estimator is particularly easy to calculate, as many packages will have the chi-squared distribution built in.)

Solution:

By (a), we have

$$E\{\pi_{\theta}(\theta | x, a, b)\} = \frac{\int_y^{\infty} \frac{1}{\theta^{n+a}} e^{-\frac{1}{b\theta}} d\theta}{\int_y^{\infty} \frac{1}{\theta^{n+a+1}} e^{-\frac{1}{b\theta}} d\theta}.$$

First, we consider a transformation

$$s = \frac{2}{b\theta} \Rightarrow ds = -\frac{2}{b\theta^2} d\theta .$$

We apply this transformation to the numerator, we have

$$\begin{aligned} \int_y^\infty \frac{1}{\theta^{n+a}} e^{-\frac{1}{b\theta}} d\theta &= -\frac{b}{2} \int_y^\infty \frac{1}{\theta^{n+a-2}} e^{-\frac{1}{b\theta}} \left(-\frac{2}{b\theta^2} \right) d\theta = -\frac{b}{2} \int_{2/by}^0 \left(\frac{b}{2} \right)^{n+a-2} s^{n+a-2} e^{-\frac{s}{2}} ds \\ &= b^{n+a-1} \Gamma(n+a-1) \int_0^{2/by} \frac{1}{\Gamma(n+a-1) 2^{n+a-1}} s^{n+a-2} e^{-\frac{s}{2}} ds \\ &= b^{n+a-1} \Gamma(n+a-1) \Pr(\chi_{2(n+a-1)}^2 < 2/by) . \end{aligned}$$

Similarly, we apply this transformation to the denominator, we obtain

$$\int_y^\infty \frac{1}{\theta^{n+a+1}} e^{-\frac{1}{b\theta}} d\theta = b^{n+a} \Gamma(n+a) \Pr(\chi_{2(n+a)}^2 < 2/by) .$$

Therefore, the Bayes estimator can be expressed as

$$\begin{aligned} E\{ \pi_\theta(\theta | x, a, b) \} &= \frac{\int_y^\infty \frac{1}{\theta^{n+a}} e^{-\frac{1}{b\theta}} d\theta}{\int_y^\infty \frac{1}{\theta^{n+a+1}} e^{-\frac{1}{b\theta}} d\theta} = \frac{b^{n+a-1} \Gamma(n+a-1) \Pr(\chi_{2(n+a-1)}^2 < 2/by)}{b^{n+a} \Gamma(n+a) \Pr(\chi_{2(n+a)}^2 < 2/by)} \\ &= \frac{1}{b(n+a-1)} \frac{\Pr(\chi_{2(n+a-1)}^2 < 2/by)}{\Pr(\chi_{2(n+a)}^2 < 2/by)} . \end{aligned}$$

Problem 3.9

For the natural exponential family $p_\eta(x)$ of (3.3.18) and the conjugate prior

$\pi(\eta|k, \mu)$ of (3.3.19) establish that:

(a) $E(X) = A'(\eta)$ and $\text{var}(X) = A''(\eta)$, where the expectation is with respect to the sampling density $p_\eta(x)$.

Solution:

The natural exponential family $p_\eta(x)$ of (3.3.18) is

$$p_\eta(x) = e^{\eta x - A(\eta)} h(x), \quad -\infty < x < \infty.$$

Since it is a density function, we have

$$\begin{aligned} \int_{-\infty}^{\infty} p_\eta(x) dx = 1 &\Rightarrow \int_{-\infty}^{\infty} e^{\eta x - A(\eta)} h(x) dx = 1 \Rightarrow \frac{\partial}{\partial \eta} \int_{-\infty}^{\infty} e^{\eta x - A(\eta)} h(x) dx = 0 \\ &\Rightarrow \int_{-\infty}^{\infty} \frac{\partial}{\partial \eta} e^{\eta x - A(\eta)} h(x) dx = 0 \Rightarrow \int_{-\infty}^{\infty} \{x - A'(\eta)\} e^{\eta x - A(\eta)} h(x) dx = 0 \\ &\Rightarrow \int_{-\infty}^{\infty} x e^{\eta x - A(\eta)} h(x) dx = A'(\eta) \int_{-\infty}^{\infty} e^{\eta x - A(\eta)} h(x) dx \Rightarrow E(X) = A'(\eta). \end{aligned}$$

Similarly,

$$\begin{aligned} \int_{-\infty}^{\infty} p_\eta(x) dx = 1 &\Rightarrow \int_{-\infty}^{\infty} e^{\eta x - A(\eta)} h(x) dx = 1 \Rightarrow \frac{\partial^2}{\partial \eta^2} \int_{-\infty}^{\infty} e^{\eta x - A(\eta)} h(x) dx = 0 \\ &\Rightarrow \int_{-\infty}^{\infty} \frac{\partial^2}{\partial \eta^2} e^{\eta x - A(\eta)} h(x) dx = 0 \Rightarrow \int_{-\infty}^{\infty} \frac{\partial}{\partial \eta} \{x - A'(\eta)\} e^{\eta x - A(\eta)} h(x) dx = 0 \\ &\Rightarrow \int_{-\infty}^{\infty} [-A''(\eta) + \{x - A'(\eta)\}^2] e^{\eta x - A(\eta)} h(x) dx = 0 \\ &\Rightarrow \int_{-\infty}^{\infty} \{x - A'(\eta)\}^2 e^{\eta x - A(\eta)} h(x) dx = A''(\eta) \int_{-\infty}^{\infty} e^{\eta x - A(\eta)} h(x) dx \Rightarrow \text{var}(X) = A''(\eta). \end{aligned}$$

Hence we have shown

$$E(X) = A'(\eta) \text{ and } \text{var}(X) = A''(\eta).$$

(b) $E\{A'(\eta)\} = \mu$ and $\text{var}\{A'(\eta)\} = E\{A''(\eta)\}/k$, where the expectation is with respect to the prior distribution.

Solution:

The prior distribution of (3.3.19) is

$$\pi(\eta | k, \mu) = c(k, \mu) e^{k\eta\mu - kA(\eta)}.$$

Suppose the support of η is (a, b) , then $e^{k\eta\mu - kA(\eta)} \rightarrow 0$ as $\eta \rightarrow a$ or b . Let

$$u = c(k, \mu) e^{k\eta\mu} \Rightarrow du = c(k, \mu) k\mu e^{k\eta\mu} d\eta, \quad v = \frac{-1}{k} e^{-kA(\eta)} \Rightarrow dv = A'(\eta) e^{-kA(\eta)} d\eta.$$

Therefore, by the method of integration by parts, we have

$$\begin{aligned} E\{A'(\eta)\} &= \int A'(\eta) c(k, \mu) e^{k\eta\mu - kA(\eta)} d\eta \\ &= \int u dv \\ &= [uv]_a^b - \int v du \\ &= \left[\frac{-1}{k} c(k, \mu) e^{k\eta\mu - kA(\eta)} \right]_a^b + \int \frac{1}{k} \cdot k\mu c(k, \mu) e^{k\eta\mu - kA(\eta)} d\eta \\ &= \mu \int c(k, \mu) e^{k\eta\mu - kA(\eta)} d\eta \\ &= \mu. \end{aligned}$$

Hence we obtain the result

$$E\{A'(\eta)\} = \mu.$$

We have

$$\begin{aligned}
\text{var}\{A'(\eta)\} &= E[\{A'(\eta) - \mu\}^2] \\
&= \int \{A'(\eta) - \mu\}^2 c(k, \mu) e^{k\eta\mu - kA(\eta)} d\eta \\
&= \int \{A'(\eta)^2 + \mu^2 - 2A'(\eta)\mu\} c(k, \mu) e^{k\eta\mu - kA(\eta)} d\eta \\
&= \int A'(\eta)^2 c(k, \mu) e^{k\eta\mu - kA(\eta)} d\eta + \mu^2 - 2\mu^2 \\
&= \int \left\{A'(\eta)^2 - \frac{1}{k}A''(\eta)\right\} c(k, \mu) e^{k\eta\mu - kA(\eta)} d\eta - \mu^2 + \frac{E\{A''(\eta)\}}{k}.
\end{aligned}$$

Let

$$\begin{aligned}
u &= c(k, \mu) e^{k\eta\mu} \Rightarrow du = c(k, \mu) k\mu e^{k\eta\mu} d\eta, \\
v &= -\frac{1}{k} A'(\eta) e^{-kA(\eta)} \Rightarrow dv = \left(A'(\eta)^2 - \frac{1}{k} A''(\eta)\right) e^{-kA(\eta)} d\eta.
\end{aligned}$$

Therefore, by the method of integration by parts, we have

$$\begin{aligned}
&\int \left\{A'(\eta)^2 - \frac{1}{k} A''(\eta)\right\} c(k, \mu) e^{k\eta\mu - kA(\eta)} d\eta - \mu^2 + \frac{E\{A''(\eta)\}}{k} \\
&= \int u dv - \mu^2 + \frac{E\{A''(\eta)\}}{k} \\
&= [uv]_a^b - \int v du - \mu^2 + \frac{E\{A''(\eta)\}}{k} \\
&= \left[-\frac{1}{k} A'(\eta) c(k, \mu) e^{k\eta\mu - kA(\eta)}\right]_a^b \\
&\quad + \int \frac{1}{k} \cdot k\mu A'(\eta) c(k, \mu) e^{k\eta\mu - kA(\eta)} d\eta - \mu^2 + \frac{E\{A''(\eta)\}}{k} \\
&= \mu \int A'(\eta) c(k, \mu) e^{k\eta\mu - kA(\eta)} d\eta - \mu^2 + \frac{E\{A''(\eta)\}}{k} \\
&= \mu^2 - \mu^2 + \frac{E\{A''(\eta)\}}{k} \\
&= \frac{E\{A''(\eta)\}}{k}.
\end{aligned}$$

Hence we obtain the result

$$\text{var}\{A'(\eta)\} = E\{A''(\eta)\} / k$$

Problem 6.4 [p.295]

(a)

Let

$$X_i | \theta \sim N(\theta, \sigma^2), \sigma^2 \text{ is known and } \theta \sim N(0, \tau^2), \tau^2 \text{ is unknown.}$$

Then the marginal distribution (6.6.4) is

$$\begin{aligned}
 m(x | \tau^2) &= \int_{-\infty}^{\infty} \prod_{i=1}^p f(x_i | \theta) \pi(\theta) d\theta \\
 &= \int_{-\infty}^{\infty} \left(\frac{1}{\sqrt{2\pi\sigma^2}} \right)^p \frac{1}{\sqrt{2\pi\tau^2}} \exp \left\{ -\sum_{i=1}^p \frac{(x_i - \theta)^2}{2\sigma^2} - \frac{\theta^2}{2\tau^2} \right\} d\theta \\
 &= \left(\frac{1}{\sqrt{2\pi}} \right)^{p+1} \frac{1}{\sigma^p \tau} \int_{-\infty}^{\infty} \exp \left\{ \frac{-1}{2\sigma^2} \sum_{i=1}^p x_i^2 + \frac{\theta}{\sigma^2} \sum_{i=1}^p x_i - \frac{p\theta^2}{2\sigma^2} - \frac{\theta^2}{2\tau^2} \right\} d\theta \\
 &= \left(\frac{1}{\sqrt{2\pi}} \right)^{p+1} \frac{1}{\sigma^p \tau} \exp \left\{ \frac{-1}{2\sigma^2} \sum_{i=1}^p x_i^2 \right\} \int_{-\infty}^{\infty} \exp \left\{ -\frac{1}{2} \left[\left(\frac{p}{\sigma^2} + \frac{1}{\tau^2} \right) \theta^2 - \frac{2p\bar{x}}{\sigma^2} \theta \right] \right\} d\theta \\
 &= \left(\frac{1}{\sqrt{2\pi}} \right)^{p+1} \frac{1}{\sigma^p \tau} \exp \left\{ \frac{-1}{2\sigma^2} \sum_{i=1}^p x_i^2 \right\} \int_{-\infty}^{\infty} \exp \left\{ -\frac{1}{2} \left(\frac{p}{\sigma^2} + \frac{1}{\tau^2} \right) \left(\theta^2 - \frac{2\bar{x}p/\sigma^2}{p/\sigma^2 + 1/\tau^2} \theta \right) \right\} d\theta \\
 &= \left(\frac{1}{\sqrt{2\pi}} \right)^{p+1} \frac{1}{\sigma^p \tau} \exp \left\{ \frac{-1}{2\sigma^2} \sum_{i=1}^p x_i^2 + \frac{\bar{x}^2 p^2 / \sigma^4}{2(p/\sigma^2 + 1/\tau^2)} \right\} \\
 &\quad \times \int_{-\infty}^{\infty} \exp \left\{ -\frac{1}{2} \left(\frac{p}{\sigma^2} + \frac{1}{\tau^2} \right) \left(\theta - \frac{\bar{x}p/\sigma^2}{p/\sigma^2 + 1/\tau^2} \right)^2 \right\} d\theta \\
 &= \left(\frac{1}{\sqrt{2\pi}} \right)^p \frac{1}{\sigma^p \tau} \exp \left\{ \frac{-1}{2\sigma^2} \sum_{i=1}^p x_i^2 + \frac{\bar{x}^2 p^2 / \sigma^4}{2(p/\sigma^2 + 1/\tau^2)} \right\} \left(\frac{p}{\sigma^2} + \frac{1}{\tau^2} \right)^{\frac{1}{2}} \\
 &\quad \times \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \left(\frac{p}{\sigma^2} + \frac{1}{\tau^2} \right)^{\frac{1}{2}} \exp \left\{ -\frac{1}{2} \left(\frac{p}{\sigma^2} + \frac{1}{\tau^2} \right) \left(\theta - \frac{\bar{x}p/\sigma^2}{p/\sigma^2 + 1/\tau^2} \right)^2 \right\} d\theta \\
 &= \left(\frac{1}{\sqrt{2\pi}} \right)^p \frac{1}{\sigma^p \tau} \left(\frac{\sigma^2 \tau^2}{p\tau^2 + \sigma^2} \right)^{\frac{1}{2}} \exp \left\{ \frac{-1}{2\sigma^2} \left(\sum_{i=1}^p x_i^2 - p\bar{x}^2 \right) - \frac{p\bar{x}^2}{2\sigma^2} + \frac{\bar{x}^2 p^2 / \sigma^4}{2(p/\sigma^2 + 1/\tau^2)} \right\}
 \end{aligned}$$

$$\begin{aligned}
&= \left(\frac{1}{2\pi\sigma} \right)^{\frac{p}{2}} \left(\frac{\sigma^2}{p\tau^2 + \sigma^2} \right)^{\frac{1}{2}} \exp \left\{ \frac{-1}{2\sigma^2} \sum_{i=1}^p (x_i - \bar{x})^2 + \frac{\bar{x}^2 p^2 / \sigma^2 - \bar{x}^2 p^2 / \sigma^2 - \bar{x}^2 p / \tau^2}{2\sigma^2 (p / \sigma^2 + 1 / \tau^2)} \right\} \\
&= \left(\frac{1}{2\pi\sigma} \right)^{\frac{p}{2}} \left(\frac{\sigma^2}{p\tau^2 + \sigma^2} \right)^{\frac{1}{2}} \exp \left\{ \frac{-1}{2\sigma^2} \sum_{i=1}^p (x_i - \bar{x})^2 - \frac{\bar{x}^2 p / \tau^2}{2\sigma^2 (p / \sigma^2 + 1 / \tau^2)} \right\} \\
&= \left(\frac{1}{2\pi\sigma} \right)^{\frac{p}{2}} \left(\frac{\sigma^2}{p\tau^2 + \sigma^2} \right)^{\frac{1}{2}} \exp \left\{ \frac{-1}{2} \left(\sum_{i=1}^p \frac{(x_i - \bar{x})^2}{\sigma^2} + \frac{p\bar{x}^2}{p\tau^2 + \sigma^2} \right) \right\}.
\end{aligned}$$

Hence we obtain the marginal distribution

$$m(x | \tau^2) = \left(\frac{1}{2\pi\sigma} \right)^{\frac{p}{2}} \left(\frac{\sigma^2}{p\tau^2 + \sigma^2} \right)^{\frac{1}{2}} \exp \left\{ \frac{-1}{2} \left(\sum_{i=1}^p \frac{(x_i - \bar{x})^2}{\sigma^2} + \frac{p\bar{x}^2}{p\tau^2 + \sigma^2} \right) \right\}.$$