

HW6 solution

7.2.1 Recall that for the model discussed in Example 7.1.1, the posterior distribution of θ was $\text{Beta}(n\bar{x} + \alpha, n(1 - \bar{x}) + \beta)$. The posterior density is then given by

$$\pi_{\theta|x_1, \dots, x_n} = \frac{\Gamma(\alpha + \beta + n)}{\Gamma(n\bar{x} + \alpha) \Gamma(n(1 - \bar{x}) + \beta)} \theta^{n\bar{x} + \alpha - 1} (1 - \theta)^{n(1 - \bar{x}) + \beta - 1}$$

The posterior mean is given by

$$\begin{aligned} E(\theta^m | x_1, \dots, x_n) &= \int_0^1 \frac{\Gamma(\alpha + \beta + n)}{\Gamma(n\bar{x} + \alpha) \Gamma(n(1 - \bar{x}) + \beta)} \theta^{n\bar{x} + \alpha + m - 1} (1 - \theta)^{n(1 - \bar{x}) + \beta - 1} d\theta \\ &= \frac{\Gamma(\alpha + \beta + n) \Gamma(n\bar{x} + \alpha + m)}{\Gamma(n\bar{x} + \alpha) \Gamma(\alpha + \beta + n + m)}. \end{aligned}$$

7.2.2 Recall that for the model discussed in Example 7.1.2 the posterior distribution of μ is

$$N\left(\left(\frac{1}{\tau_0^2} + \frac{n}{\sigma_0^2}\right)^{-1} \left(\frac{\mu_0}{\tau_0^2} + \frac{n}{\sigma_0^2} \bar{x}\right), \left(\frac{1}{\tau_0^2} + \frac{n}{\sigma_0^2}\right)^{-1}\right)$$

By exercise 2.6.3, the posterior distribution of the third quartile $\Psi = \mu + \sigma_0 z_{0.75}$ is

$$N\left(\left(\frac{1}{\tau_0^2} + \frac{n}{\sigma_0^2}\right)^{-1} \left(\frac{\mu_0}{\tau_0^2} + \frac{n}{\sigma_0^2} \bar{x}\right) + \sigma_0 z_{0.75}, \left(\frac{1}{\tau_0^2} + \frac{n}{\sigma_0^2}\right)^{-1}\right)$$

Since the normal distribution is symmetric about its mode and the mean exists, the posterior mode and mean agree and given by

$$\hat{\psi} = \left(\frac{1}{\tau_0^2} + \frac{n}{\sigma_0^2}\right)^{-1} \left(\frac{\mu_0}{\tau_0^2} + \frac{n}{\sigma_0^2} \bar{x}\right) + \sigma_0 z_{0.75}.$$

7.2.6 Recall that the posterior distribution of θ in Example 7.2.2 is $\text{Beta}(n\bar{x} + \alpha, n(1 - \bar{x}) + \beta)$. To find the posterior variance we need only to find the second moment as follows.

$$\begin{aligned}
& E(\theta^2 | x_1, \dots, x_n) \\
&= \int_0^1 \theta^2 \frac{\Gamma(n + \alpha + \beta)}{\Gamma(n\bar{x} + \alpha) \Gamma(n(1 - \bar{x}) + \beta)} \theta^{n\bar{x} + \alpha - 1} (1 - \theta)^{n(1 - \bar{x}) + \beta - 1} d\theta \\
&= \frac{\Gamma(n + \alpha + \beta)}{\Gamma(n\bar{x} + \alpha) \Gamma(n(1 - \bar{x}) + \beta)} \int_0^1 \theta^{n\bar{x} + \alpha + 1} (1 - \theta)^{n(1 - \bar{x}) + \beta - 1} d\theta \\
&= \frac{\Gamma(n + \alpha + \beta)}{\Gamma(n\bar{x} + \alpha) \Gamma(n(1 - \bar{x}) + \beta)} \frac{\Gamma(n\bar{x} + \alpha + 2) \Gamma(n(1 - \bar{x}) + \beta)}{\Gamma(n + \alpha + \beta + 2)} \\
&= \frac{(n\bar{x} + \alpha + 1)(n\bar{x} + \alpha)}{(n + \alpha + \beta + 1)(n + \alpha + \beta)}
\end{aligned}$$

The posterior variance is then given by

$$\begin{aligned}
\text{Var}(\theta | x_1, \dots, x_n) &= E(\theta^2 | x_1, \dots, x_n) - (E(\theta | x_1, \dots, x_n))^2 \\
&= \frac{(n\bar{x} + \alpha + 1)(n\bar{x} + \alpha)}{(n + \alpha + \beta + 1)(n + \alpha + \beta)} - \left(\frac{n\bar{x} + \alpha}{n + \alpha + \beta} \right)^2 \\
&= \frac{(n\bar{x} + \alpha)(n(1 - \bar{x}) + \beta)}{(n + \alpha + \beta + 1)(n + \alpha + \beta)^2}.
\end{aligned}$$

Now $0 \leq \bar{x} \leq 1$, so

$$\begin{aligned}
\text{Var}(\theta | x_1, \dots, x_n) &= \frac{(n\bar{x} + \alpha)(n(1 - \bar{x}) + \beta)}{(n + \alpha + \beta + 1)(n + \alpha + \beta)^2} \\
&\leq \frac{(1 + \alpha/n)(1 + \beta/n)}{n(1 + \alpha/n + \beta/n + 1/n)(1 + \alpha/n + \beta/n)^2} \rightarrow 0
\end{aligned}$$

as $n \rightarrow \infty$.

7.2.10 The likelihood function is given by $L(\lambda|x_1, \dots, x_n) = \lambda^n e^{-n\bar{x}\lambda}$. The prior distribution has density given by $\beta_0^{\alpha_0} \lambda^{\alpha_0-1} e^{-\beta_0\lambda} / \Gamma(\alpha_0)$. The posterior density of λ is then given by $\pi(\lambda|x_1, \dots, x_n) \propto \lambda^{n+\alpha_0-1} e^{-\lambda(n\bar{x}+\beta_0)}$, and we recognize this as being the density of a $\text{Gamma}(n+\alpha_0, n\bar{x}+\beta_0)$ distribution. The posterior mean and variance of λ are then given by $E(\lambda|x_1, \dots, x_n) = (n+\alpha_0)/(n\bar{x}+\beta_0)$, $\text{Var}(\lambda|x_1, \dots, x_n) = (n+\alpha_0)/(n\bar{x}+\beta_0)^2$.

To find the posterior mode we need to maximize $\ln(\lambda^{n+\alpha_0-1} e^{-\lambda(n\bar{x}+\beta_0)}) = (\alpha_0+n-1)\ln\lambda - \lambda(n\bar{x}+\beta_0)$. This has first derivative given by $(\alpha_0+n-1)/\lambda - (n\bar{x}+\beta_0)$ and second derivative $-(\alpha_0+n-1)/\lambda^2$. Setting the first derivative equal to 0 and solving gives the solution $\hat{\lambda} = (\alpha_0+n-1)/(n\bar{x}+\beta_0)$. The second derivative at this value is $-(n\bar{x}+\beta_0)^2/(\alpha_0+n-1)$, which is clearly negative, so $\hat{\lambda}$ is the unique posterior mode.