



Problem 1

a) We have

$$\begin{aligned} f(x; \mu) &= \frac{\tau}{\sqrt{2\pi}} \exp \left\{ -\frac{\tau^2}{2} (x^2 - 2x\mu + \mu^2) \right\} \\ &= \frac{\tau \exp \left\{ -\frac{\tau^2 x^2}{2} \right\}}{\sqrt{2\pi}} \exp \left\{ \mu\tau^2 x - \frac{\tau^2 \mu^2}{2} \right\} \end{aligned}$$

Thus, we may choose for example

$$a(x) = \frac{\tau \exp \left\{ -\frac{\tau^2 x^2}{2} \right\}}{\sqrt{2\pi}}, \quad \phi(\mu) = \mu, \quad t(x) = \tau^2 x \quad \text{and} \quad b(\mu) = -\frac{\tau^2 \mu^2}{2}.$$

The conjugate prior distribution becomes

$$\pi(\mu) \propto \exp \{ \phi(\mu)\alpha + b(\mu)\beta \} = \exp \left\{ \mu\alpha - \frac{\tau^2 \mu^2}{2} \beta \right\}$$

We see that the exponent is a second order function of μ . Thus, the conjugate prior is a normal distribution.

b) With

$$\pi(\mu) = \frac{r}{\sqrt{2\pi}} \exp \left\{ -\frac{r^2}{2} (\mu - \nu)^2 \right\}$$

the posterior distribution becomes

$$\begin{aligned} \pi(\mu | x_1, \dots, x_n) &\propto \pi(\mu) \prod_{i=1}^n f(x_i; \mu) \propto \exp \left\{ -\frac{r^2}{2} (\mu - \nu)^2 - \sum_{i=1}^n \frac{\tau^2}{2} (x_i - \mu)^2 \right\} \\ &= \exp \left\{ -\frac{r^2}{2} (\mu^2 - 2\mu\nu + \nu^2) - \frac{\tau^2}{2} \sum_{i=1}^n (x_i^2 - 2x_i\mu + \mu^2) \right\} \end{aligned}$$

$$\propto \exp \left\{ -\frac{1}{2} \left[(r^2 + n\tau^2) \mu^2 - 2 \left(r^2\nu + \tau^2 \sum_{i=1}^n x_i \right) \mu \right] \right\}.$$

As expected from the results in **a)** we see that this is a normal distribution. To find $E[\mu|x_1, \dots, x_n]$ and $\text{Var}[\mu|x_1, \dots, x_n]$ define $\tilde{\nu} = E[\mu|x_1, \dots, x_n]$ and $\tilde{r}^2 = 1/\text{Var}[\mu|x_1, \dots, x_n]$. We then must have

$$\pi(\mu|x_1, \dots, x_n) \propto \exp \left\{ -\frac{\tilde{r}^2}{2} (\mu - \tilde{\nu})^2 \right\} \propto \exp \left\{ -\frac{1}{2} [\tilde{r}^2 \mu^2 - 2\tilde{r}^2 \tilde{\nu} \mu] \right\}.$$

Thus, we must have

$$\tilde{r}^2 = r^2 + n\tau^2 \quad \text{and} \quad \tilde{r}^2 \tilde{\nu} = r^2\nu + \tau^2 \sum_{i=1}^n x_i.$$

Solving with respect to $\tilde{\nu}$ and $\tilde{r}^2$ we get

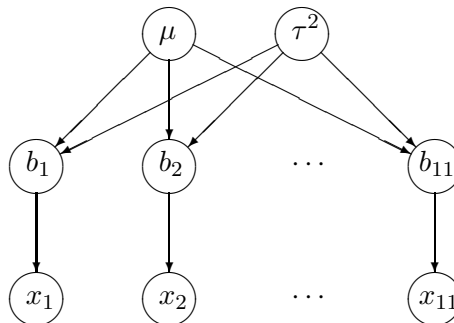
$$\tilde{\nu} = \frac{r^2\nu + \tau^2 \sum_{i=1}^n x_i}{r^2 + n\tau^2} \quad \text{and} \quad \tilde{r}^2 = r^2 + n\tau^2$$

and we get

$$E[\mu|x_1, \dots, x_n] = \frac{r^2\nu + \tau^2 \sum_{i=1}^n x_i}{r^2 + n\tau^2} \quad \text{and} \quad \text{Var}[\mu|x_1, \dots, x_n] = \frac{1}{r^2 + n\tau^2}.$$

Problem 2

a) The graphical model becomes



The full posterior distribution for μ is

$$\pi(\mu|\tau^2, b_1, \dots, b_{11}, x_1, \dots, x_{11}) \propto \pi(\mu) \prod_{i=1}^{11} \pi(b_i; \mu, \tau^2),$$

where $\pi(\mu)$ is a $N(\nu, 1/r^2)$ distribution and $\pi(b_i; \mu, \tau^2)$ is a $N(\mu, 1/\tau^2)$ distribution. This is the same situation as discussed in Problem 1, except the $x_1, \dots, x_n$ in Problem 1 is now replaced by $b_1, \dots, b_{11}$. Thus, we have

$$\mu | \tau^2, b_1, \dots, b_{11}, x_1, \dots, x_{11} \sim N \left(\frac{r^2 \nu + \tau^2 \sum_{i=1}^{11} b_i}{r^2 + 11\tau^2}, \frac{1}{r^2 + 11\tau^2} \right).$$

Using this as a proposal distribution is a Gibbs step, in which case the acceptance probability becomes equal to one.

The full conditional distribution for τ^2 becomes

$$\begin{aligned} \pi(\tau^2 | \mu, b_1, \dots, b_{11}, x_1, \dots, x_{11}) &\propto \pi(\tau^2) \prod_{i=1}^{11} \pi(b_i | \mu, \tau^2) \\ &\propto (\tau^2)^{\alpha-1} \exp \left\{ -\frac{\tau^2}{\beta} \right\} \prod_{i=1}^{11} \tau \exp \left\{ -\frac{\tau^2}{2} (b_i - \mu)^2 \right\} \\ &= (\tau^2)^{\alpha+11/2-1} \exp \left\{ -\frac{\tau^2}{\left(1/\beta + \frac{1}{2} \sum_{i=1}^{11} (b_i - \mu)^2 \right)^{-1}} \right\} \end{aligned}$$

Comparing this expression with the density of a gamma distribution we see that this is a gamma distribution with parameters

$$\underline{\underline{\tilde{\alpha} = \alpha + \frac{11}{2} \quad \text{and} \quad \tilde{\beta} = \frac{1}{\frac{1}{\beta} + \frac{1}{2} \sum_{i=1}^{11} (b_i - \mu)^2}}}}.$$

b) The density of the proposal distribution is

$$q(\tilde{b}_i | b_i) = \begin{cases} \frac{1}{2a} & \text{for } \tilde{b}_i \in [b_i - a, b_i + a], \\ 0 & \text{otherwise.} \end{cases}$$

The acceptance probability is only of interest when $\tilde{b}_i \in [b_i - a, b_i + a]$, in which case $q(\tilde{b}_i | b_i) = 1/(2a) = q(b_i | \tilde{b}_i)$ and the acceptance probability becomes

$$\begin{aligned} \alpha(\tilde{b}_i | b_i) &= \min \left\{ 1, \frac{\pi(b_1, \dots, b_{i-1}, \tilde{b}_i, b_{i+1}, \dots, b_{11}, \mu, \tau^2 | x_1, \dots, x_{11})}{\pi(b_1, \dots, b_{i-1}, b_i, b_{i+1}, \dots, b_{11}, \mu, \tau^2 | x_1, \dots, x_{11})} \cdot \frac{q(b_i | \tilde{b}_i)}{q(\tilde{b}_i | b_i)} \right\} \\ &= \min \left\{ 1, \frac{\pi(\tilde{b}_i | \mu, \tau^2) \pi(x_i | \tilde{b}_i)}{\pi(b_i | \mu, \tau^2) \pi(x_i | b_i)} \right\} \end{aligned}$$

$$= \min \left\{ 1, \exp \left\{ -\frac{\tau^2}{2} \left((\tilde{b}_i - \mu)^2 - (b_i - \mu)^2 \right) \right\} \frac{\tilde{p}_i^{x_i} (1 - \tilde{p}_i)^{n_i - x_i}}{p_i^{x_i} (1 - p_i)^{n_i - x_i}} \right\},$$

where $p_i = 1/(1 + e^{b_i})$ and $\tilde{p}_i = 1/(1 + e^{\tilde{b}_i})$.

With proposal distribution $\tilde{b}_i \sim \text{Unif}[b_i - 2a, b_i + a]$ the density of the proposal distribution becomes

$$q(\tilde{b}_i | b_i) = \begin{cases} \frac{1}{3a} & \text{for } \tilde{b}_i \in [b_i - 2a, b_i + a], \\ 0 & \text{otherwise.} \end{cases}$$

When $\tilde{b}_i \in [b_i - a, b_i + a]$ we then have $q(\tilde{b}_i | b_i) = 1/(3a) = q(b_i | \tilde{b}_i)$ and the acceptance probability is given by the same formula as above. When $\tilde{b}_i \in [b_i - 2a, b_i - a]$ we have $q(b_i | \tilde{b}_i) = 0$ and thereby $\alpha(\tilde{b}_i | b_i) = 0$. Thus, using computation time to propose values $\tilde{b}_i \in [b_i - 2a, b_i - a]$ is a waste of computing time.

c) Of the three values for a tried it is preferable to use $a = 1.0$ as the estimated autocorrelation function is falling the fastest in this case. For $a = 4$ we can also observe that the simulated Markov chain has a very low acceptance probability for b_1 , which is not a favourable property.

To decide the value of a one should also have studied corresponding plots for the other simulated values, $b_2, \dots, b_{11}, \mu$ and τ^2 . It is also natural to monitor the acceptance rates (for the b_i 's) with the goal to get the acceptance rates close to 0.234.

d) First one needs to find the length of the burn-in phase of the chain. This can be done by output analysis. Assume the Markov chain has (essentially) converged after $T < M$ iterations.

1. $E[p_i | x_1, \dots, x_{11}]$ can then be estimated by

$$\widehat{E}[p_i | x_1, \dots, x_{11}] = \frac{1}{M - T + 1} \sum_{m=T}^M \frac{e^{b_i^m}}{1 + e^{b_i^m}}$$

2. $\text{Prob}(p_i < p_j | x_1, \dots, x_n)$ can be estimated by

$$\begin{aligned} \widehat{\text{Prob}}(p_i < p_j | x_1, \dots, x_n) &= \frac{1}{M - T + 1} \sum_{m=T}^M I \left(\frac{e^{b_i^m}}{1 + e^{b_i^m}} < \frac{e^{b_j^m}}{1 + e^{b_j^m}} \right) \\ &= \frac{1}{M - T + 1} \sum_{m=T}^M I(b_i^m < b_j^m) \end{aligned}$$

3. $\text{Prob}(p_i < \min_{j \neq i} p_j | x_1, \dots, x_{11})$ can be estimated by

$$\widehat{\text{Prob}}(p_i < \min_{j \neq i} p_j | x_1, \dots, x_n) = \frac{1}{M - T - 1} \sum_{m=T}^M I \left(b_i^m < \min_{j \neq i} b_j^m \right)$$

To find the best hospital given our data let us consider the outcome of a new surgery in each of the hospitals. Let y_i denote the result of the next surgery in hospital H_i , $y_i = 1$ if this surgery results in a death and $y_i = 0$ otherwise. To find the best hospital we then need to minimise

$$\begin{aligned} \text{Prob}(y_i = 1 | x_1, \dots, x_{11}) &= \int_{-\infty}^{\infty} \text{Prob}(y_i = 1 | p_i, x_1, \dots, x_{11}) \pi(p_i | x_1, \dots, x_{11}) dp_i \\ &= \int_{-\infty}^{\infty} \text{Prob}(y_i = 1 | p_i) \pi(p_i | x_1, \dots, x_{11}) dp_i = \int_{-\infty}^{\infty} p_i \pi(p_i | x_1, \dots, x_{11}) dp_i = E[p_i | x_1, \dots, x_{11}]. \end{aligned}$$

Thus, our estimated best hospital is the hospital with the lowest value for $\widehat{E}[p_i | x_1, \dots, x_{11}]$.

Problem 3

a) Our estimated model is

$$x_i^* \sim \text{bin}(n_i, \widehat{p}_i).$$

The bootstrap replication of $\widehat{p}_i$ becomes

$$\widehat{p}_i^* = \frac{x_i^*}{n_i}.$$

The ideal bootstrap estimator for the standard deviation of $\widehat{p}_i$ is thereby

$$\underline{\underline{\text{SD}_{\widehat{F}_{\text{par}}}[\widehat{p}_i^*]}}.$$

Compute first the corresponding variance,

$$\text{Var}_{\widehat{F}_{\text{par}}}[\widehat{p}_i^*] = \text{Var}_{\widehat{F}_{\text{par}}} \left[\frac{x_i^*}{n_i} \right] = \frac{\text{Var}_{\widehat{F}_{\text{par}}}[x_i^*]}{n_i^2} = \frac{n_i \widehat{p}_i (1 - \widehat{p}_i)}{n_i^2} = \frac{\widehat{p}_i (1 - \widehat{p}_i)}{n_i}.$$

The ideal bootstrap estimator for the standard deviation of $\widehat{p}_i$ is thereby

$$\underline{\underline{\text{SD}_{\widehat{F}_{\text{par}}}[\widehat{p}_i^*] = \sqrt{\frac{\widehat{p}_i (1 - \widehat{p}_i)}{n_i}}.}}$$

b) The pseudo code becomes:

1. For $b = 1, \dots, B$ and $i = 1, \dots, 11$ generate $x_i^{*b} \sim \text{bin}(n_i, \hat{p}_i)$ independently.
2. For $b = 1, \dots, B$ and $i = 1, \dots, 11$ compute

$$\hat{p}_i^{*b} = \frac{x_i^{*b}}{n_i}.$$

3. For each of $b = 1, \dots, B$ order $\hat{p}_1^{*b}, \dots, \hat{p}_{11}^{*b}$ from smallest to largest and let $\hat{r}_i^{*b}$ denote the rank of $\hat{p}_i^{*b}$ for $i = 1, \dots, 11$.
4. For each of $i = 1, \dots, 11$ order $\hat{r}_i^{*1}, \dots, \hat{r}_i^{*B}$ from smallest to largest and let $\hat{r}_i^{*(k)}$ denote the k 'th smallest value.
5. For each of $i = 1, \dots, 11$, the $(1 - \alpha) \cdot 100\%$ percentile interval for r_i is

$$\underline{\underline{[\hat{r}_i^{*(B\alpha/2)}, \hat{r}_i^{*(B(1-\alpha/2))}]}.$$

That r_i takes only integer values is not important for the procedure except that it then requires that the interval is defined as a closed interval.