

3. full conditional for  $\beta$ :

prior on  $\beta$ :

$$\beta \sim \text{MVN}_{p+1}(\mu_\beta, \Sigma_\beta)$$

$$y \sim \text{MVN}_n(X\beta + \theta, \sigma^2 I_n)$$

$$\pi(\beta|\dots) \propto f(D|\dots) \pi(\beta)$$

$$\propto \frac{1}{(2\pi)^{n/2} |\Sigma|^{1/2}} \exp \left\{ -\frac{1}{2} (y - X\beta - \theta)^T \Sigma^{-1} (y - X\beta - \theta) \right\}$$

$$\frac{1}{(2\pi)^{(p+1)/2} |\Sigma_\beta|^{1/2}} \exp \left\{ -\frac{1}{2} (\beta - \mu_\beta)^T \Sigma_\beta^{-1} (\beta - \mu_\beta) \right\}$$

$$\propto \exp \left\{ -\frac{1}{2} (y - X\beta - \theta)^T (\sigma^2 I_n)^{-1} (y - X\beta - \theta) \right\}$$

$$\exp \left\{ -\frac{1}{2} (\beta - \mu_\beta)^T \Sigma_\beta^{-1} (\beta - \mu_\beta) \right\}$$

$$\propto \exp \left\{ -\frac{1}{2} \left[ \frac{1}{\sigma^2} (-y^T X \beta - \beta^T X^T y + \beta^T X^T X \beta + \beta^T X^T \theta + \theta^T X \beta) + (\beta^T \Sigma_\beta^{-1} \beta - \beta^T \Sigma_\beta^{-1} \mu_\beta - \mu_\beta^T \Sigma_\beta^{-1} \beta) \right] \right\}$$

$$\propto \exp \left\{ -\frac{1}{2} \left[ \frac{1}{\sigma^2} (\beta^T X^T X \beta - 2y^T X \beta + 2\theta^T X \beta) + (\beta^T \Sigma_\beta^{-1} \beta - 2\mu_\beta^T \Sigma_\beta^{-1} \beta) \right] \right\}$$

$$\propto \exp \left\{ -\frac{1}{2} \left[ \beta^T \left( \frac{X^T X}{\sigma^2} + \Sigma_\beta^{-1} \right) \beta - 2 \left( \frac{y^T X}{\sigma^2} - \frac{\theta^T X}{\sigma^2} + \mu_\beta^T \Sigma_\beta^{-1} \right) \beta \right] \right\}$$

in general,

$$\propto \exp \left\{ -\frac{1}{2} \left[ \beta^T (X^T \Sigma^{-1} X + \Sigma_\beta^{-1}) \beta - 2 (y^T \Sigma^{-1} X - \theta^T \Sigma^{-1} X + \mu_\beta^T \Sigma_\beta^{-1}) \beta \right] \right\}$$

Now, comparing the exponent term with  $\theta^T A \theta - 2b^T \theta$

$$\text{we get, } A = (X^T \Sigma^{-1} X + \Sigma_\beta^{-1})$$

$$\text{and, } b = X^T \Sigma^{-1} y - X^T \Sigma^{-1} \theta + \Sigma_\beta^{-1} \mu_\beta$$

[dispersions are symmetric]

$$\therefore \beta|\dots \sim \text{MVN}_{p+1}(A^{-1}b, A^{-1})$$

Note:  $\Sigma = \sigma^2 I_n$   
 $\Sigma_\beta = 10^4 \times I_3$



(2)

2. Full conditional for  $\sigma^2$ : prior on  $\sigma^2 \sim \text{IG}(a_0 = 2.5, b_0 = 2.5)$ .

$$\pi(\sigma^2 | \dots) \propto f(D | \dots) \pi(\sigma^2)$$

$$\propto (\sigma^2)^{-n/2} \exp \left\{ -\frac{1}{\sigma^2} \frac{(y - X\beta - \theta)^T (y - X\beta - \theta)}{2} \right\} \exp \left\{ -\frac{b_0}{\sigma^2} \right\} \cdot (\sigma^2)^{-a_0-1}$$

$$\propto (\sigma^2)^{-(n/2 + a_0) - 1} \cdot \exp \left\{ -\frac{1}{\sigma^2} \left[ \frac{(y - X\beta - \theta)^T (y - X\beta - \theta)}{2} + b_0 \right] \right\}$$

$$\text{so, } \sigma^2 | \dots \sim \text{IG} \left( \frac{n}{2} + a_0, \frac{(y - X\beta - \theta)^T (y - X\beta - \theta)}{2} + b_0 \right)$$



3. Full conditional for  $\theta$ :  $\theta \sim \text{MVN}(0, \frac{\tau^2 R}{\Sigma_\theta})$  ;  $y \sim \text{MVN}(X\beta + \theta, \Sigma = \sigma^2 I_n)$

$$\pi(\theta|\dots) \propto f(\theta|\dots) \pi(\theta|\tau^2, \lambda)$$

$$\propto |\Sigma|^{-1/2} \exp \left\{ -\frac{1}{2} (y - X\beta - \theta)^T \Sigma^{-1} (y - X\beta - \theta) \right\} \cdot |\Sigma_\theta|^{-1/2}$$

$$\exp \left\{ -\frac{1}{2} (\theta - 0)^T \Sigma_\theta^{-1} (\theta - 0) \right\}$$

$$\propto \exp \left\{ -\frac{1}{2} \left( -y^T \Sigma^{-1} \theta + \beta^T X^T \Sigma^{-1} \theta - \theta^T \Sigma^{-1} y + \theta^T \Sigma^{-1} X \beta + \theta^T \Sigma^{-1} \theta + \theta^T \Sigma_\theta^{-1} \theta \right) \right\}$$

$$\propto \exp \left\{ -\frac{1}{2} \left[ \theta^T (\Sigma^{-1} + \Sigma_\theta^{-1}) \theta - 2 (y^T \Sigma^{-1} - \beta^T X^T \Sigma^{-1}) \theta \right] \right\}$$

Comparing the exponent term with  $\theta^T A \theta - 2 b^T \theta$ , we get.

$$A = \Sigma^{-1} + \Sigma_\theta^{-1} ; \quad b = \frac{y^T \Sigma^{-1} - \beta^T X^T \Sigma^{-1}}{\Sigma^{-1}}$$

$$\therefore \theta| \dots \sim \text{MVN}(A^{-1} b, A^{-1})$$

$$\begin{cases} \Sigma = \sigma^2 I_n \\ \Sigma_\theta = \tau^2 R \end{cases}$$

where,  $R_{ij} = \delta_{ij}$  (Kronecker delta)



(4)

4. full conditional for  $\tau^2$  ; prior on  $\tau^2 \sim \text{IG} (a_\tau = 2.5, b_\tau = 2.5)$

$$\pi(\tau^2 | \dots) \propto f(D | \dots) \pi(\theta | \tau^2, \lambda) \cdot \pi(\tau^2)$$

$$\propto |\Sigma|^{-1/2} \exp \left\{ -\frac{1}{2} (Y - XB - \theta)^T \Sigma^{-1} (Y - XB - \theta) \right\} \cdot$$

$$|\Sigma_\theta|^{-1/2} \exp \left\{ -\frac{1}{2} (\theta - 0)^T \Sigma_\theta^{-1} (\theta - 0) \right\} \cdot$$

$$(\tau^2)^{-a_\tau - 1} \exp \left\{ -\frac{1}{\tau^2} b_\tau \right\}$$

$$\left| \begin{array}{l} \theta \sim \text{MVN}(0, \Sigma_\theta = \tau^2 R) \\ |\Sigma_\theta|^{-1/2} = |\tau^2 R|^{-1/2} \\ = (\tau^2)^n |R|^{-1/2} \\ = (\tau^2)^{-n/2} |R|^{-1/2} \end{array} \right.$$

$$\propto (\tau^2)^{-n/2} \cdot |R|^{-1/2} \exp \left\{ -\frac{1}{\tau^2} \left[ \frac{\theta^T R^{-1} \theta}{2} + b_\tau \right] \right\} \cdot (\tau^2)^{-a_\tau - 1}$$

$$\propto (\tau^2)^{-(n/2 + a_\tau) - 1} \exp \left\{ -\frac{1}{\tau^2} \left[ \frac{\theta^T R^{-1} \theta}{2} + b_\tau \right] \right\}$$

$$\therefore \tau^2 | \dots \sim \text{IG} \left( \frac{n}{2} + a_\tau, \frac{\theta^T R^{-1} \theta}{2} + b_\tau \right)$$



for  $\tau^2$ :  $\theta \sim \text{MVN}(\theta, \tau^2 R)$   
 $\hookrightarrow \Sigma_\theta$ .

$$|\Sigma_\theta|^{-1/2} = |\tau^2 R|^{-1/2} = ((\tau^2)^n \cdot |R|)^{-1/2} = (\tau^2)^{-n/2} |R|^{-1/2}.$$

~~for~~ FCD of  $\lambda$ :

$\rightarrow \lambda \sim \text{unif}(a, b)$

$$\pi(\lambda | \dots) \propto \pi(D | \dots) \cdot \pi(\theta | \tau^2, \lambda) \cdot \pi(\lambda)$$

$$\propto \frac{(\tau^2)^{-n/2}}{|R|^{-1/2}}$$

$$\propto |\Sigma_\theta|^{-1/2} \cdot \exp \left\{ -\frac{1}{2} \theta^T \Sigma_\theta^{-1} \theta \right\} \cdot \frac{1}{b_\lambda - a_\lambda}$$

[Likelihood  $\propto \text{MVN}(\theta | \Sigma_\theta)$  is a free, therefore ignored]

$$\propto (\tau^2)^{-n/2} \cdot |R|^{-1/2} \cdot \exp \left\{ -\frac{1}{2\tau^2} \theta^T R^{-1} \theta \right\} \cdot \frac{1}{b_\lambda - a_\lambda}$$

$$\propto |R|^{-1/2} \cdot \exp \left\{ -\frac{1}{2\tau^2} \cdot \theta^T R^{-1} \theta \right\}$$

[if all values of  $\lambda$  possess same probability]

Acceptance ratio:

$$P_A = \left( \frac{|R^*|}{|R^{(i)}|} \right)^{-1/2} \cdot \exp \left\{ -\frac{1}{2\tau^2} \theta^T (R^{*-1} - R^{(i)-1}) \theta \right\}$$

$$\Rightarrow \ln(P_A) = -\frac{1}{2} (\ln |R^*| - \ln |R^{(i)}|) - \frac{1}{2\tau^2} \theta^T (R^{*-1} - R^{(i)-1}) \theta$$

$$\text{if } \ln(\text{unif}) < \ln(P_A)$$

accept  $\lambda^*$ , otherwise  $\lambda^{(i+1)} = \lambda^{(i)}$

Here,  $R_{ij}^* = e^{-\lambda^* d(s_i, s_j)}$

and  $R_{ij}^{(i)} = e^{-\lambda^{(i)} d(s_i, s_j)}$