

Posterior distribution generation

1 The model:

The main model is:

$$Y_i(t+6) = \beta_{0,i} + x_{i,1}\beta_{1,i} + x_{i,2}\beta_{2,i} + x_{i,3}\beta_{3,i} + \beta_{4,i}Y_i(t) \\ + \beta_{5,i}\Delta_{i,1}(t) + \beta_{6,i}\Delta_{i,2}(t) + \beta_{7,i}\Delta_{i,3} + \epsilon_i(t)$$

(NOTE: omit j as we don't know what it is for now)

1. $x_{i,1}$ is the month of year when the hurricane started
2. $x_{i,2}$ is the calendar year of the hurricane
3. $x_{i,3}$ is the type of hurricane
4. $\Delta_{i,1}(t)$, $\Delta_{i,2}(t)$ and $\Delta_{i,3}(t)$ is the change of latitude longitude, and wind speed between $t - 6$ and t
5. $\epsilon_{i,t}$ follows a normal distributions with mean zero and variance σ^2 , independent across t

2 Distribution and priors:

Marginal distributions:

$$f((Y_{i,t+6})|\mu_i, \sigma) \sim N(\mu_{i,t}, \sigma^2) \\ \boldsymbol{\beta}_i \sim N(\boldsymbol{\beta}, \boldsymbol{\Sigma})$$

Priors:

$$f(\sigma^2) \propto \frac{1}{\sigma^2} \\ f(\boldsymbol{\beta}) \propto 1 \\ f(\boldsymbol{\Sigma}^{-1}) \propto |\boldsymbol{\Sigma}|^{-d-1} \exp\left\{-\frac{1}{2}\boldsymbol{\Sigma}^{-1}\right\}$$

3 Hierarchical model structure:

Denote $\mathbf{Y} = \{Y_{i,t}\}, i = 1, 2, \dots, n, t = 1, 2, \dots, t_i$.

Hierarchical model will be:

$$\begin{aligned} f(\boldsymbol{\beta}, \boldsymbol{\beta}_i, \boldsymbol{\Sigma}^{-1}, \sigma^2 | \mathbf{Y}) &\propto f(\mathbf{Y} | \boldsymbol{\beta}_i, \sigma^2) f(\boldsymbol{\beta}_i | \boldsymbol{\beta}, \boldsymbol{\Sigma}^{-1}) f(\boldsymbol{\beta}) f(\boldsymbol{\Sigma}^{-1}) f(\sigma^2) \\ f(\mathbf{Y} | \boldsymbol{\beta}_i, \sigma) &\propto \prod_{i=1}^n \prod_{t=1}^{t_i} \sigma^{-1} \exp\left\{-\frac{(Y_{i,t} - \mu_{i,t})^2}{2\sigma^2}\right\} \\ f(\boldsymbol{\beta}_i | \boldsymbol{\beta}, \boldsymbol{\Sigma}^{-1}) &\propto \prod_{i=1}^n \frac{1}{\sqrt{|\boldsymbol{\Sigma}|}} \exp\left\{-\frac{1}{2}(\boldsymbol{\beta}_i - \boldsymbol{\beta})^T \boldsymbol{\Sigma}^{-1} (\boldsymbol{\beta}_i - \boldsymbol{\beta})\right\} \end{aligned}$$

After put all element into the formula, the full posteria will be the mutiplication of all terms

4 Posterior Distribution Inference:

1. For $\pi(\boldsymbol{\beta}_i | \cdot)$:

Let:

$$\begin{aligned} \mathbf{Y}_i &= (Y_{i,1}, Y_{i,2}, \dots, Y_{i,t_i})^T \\ \mathbf{X}_i &= \begin{bmatrix} x_{i,1,1} & x_{i,2,1} & \cdots & x_{i,8,1} \\ x_{i,1,2} & x_{i,2,2} & \cdots & x_{i,8,2} \\ \vdots & \vdots & \ddots & \vdots \\ x_{i,1,t_i} & x_{i,2,t_i} & \cdots & x_{i,8,t_i} \end{bmatrix}_{t_i \times 8} \end{aligned}$$

The posteria will be:

$$\begin{aligned} \pi(\boldsymbol{\beta}_i | \cdot) &\propto f(\mathbf{Y}_i | \boldsymbol{\beta}_i, \sigma^2) f(\boldsymbol{\beta}_i | \boldsymbol{\beta}, \boldsymbol{\Sigma}^{-1}) \\ &\propto \prod_{t=1}^{t_i} \left(\sigma^{-1} \exp\left\{-\frac{(Y_{i,t} - \mu_{i,t})^2}{2\sigma^2}\right\} \right) \left(\frac{1}{\sqrt{|\boldsymbol{\Sigma}|}} \exp\left\{-\frac{1}{2}(\boldsymbol{\beta}_i - \boldsymbol{\beta})^T \boldsymbol{\Sigma}^{-1} (\boldsymbol{\beta}_i - \boldsymbol{\beta})\right\} \right) \\ &\propto \exp\left\{-\frac{1}{2} \left(\sum_{t=1}^{t_i} \sigma^{-2} (Y_{i,t} - \mathbf{X}_i \boldsymbol{\beta}_i)^2 + (\boldsymbol{\beta}_i - \boldsymbol{\beta})^T \boldsymbol{\Sigma}^{-1} (\boldsymbol{\beta}_i - \boldsymbol{\beta}) \right)\right\} \\ &\propto \exp\left\{-\frac{1}{2} \left((\mathbf{Y}_i - \mathbf{X}_i \boldsymbol{\beta}_i)^T (\sigma^{-2} \mathbf{I}_{t_i \times t_i}) (\mathbf{Y}_i - \mathbf{X}_i \boldsymbol{\beta}_i) + (\boldsymbol{\beta}_i - \boldsymbol{\beta})^T \boldsymbol{\Sigma}_{8 \times 8}^{-1} (\boldsymbol{\beta}_i - \boldsymbol{\beta}) \right)\right\} \\ &\propto \exp\left\{-\frac{1}{2} [((\sigma_i^2 (X_i^T X_i)^{-1}) + \boldsymbol{\Sigma}^{-1})^{-1}] ((X_i^T X_i)^{-1} \boldsymbol{\beta} + I \sigma_i^{-2} X_i^T Y_{it})^T ((\sigma_i^2 (X_i^T X_i)^{-1} + \boldsymbol{\Sigma}^{-1}) \\ &\quad ((X_i^T X_i)^{-1} \boldsymbol{\Sigma}^{-1} \boldsymbol{\beta} + I \sigma_i^{-2} X_i^T Y_{it})) \right\} \end{aligned}$$

So:

$$\boldsymbol{\beta}_i \sim N(\mathbf{K}((X_i^T X_i)^{-1} \boldsymbol{\Sigma}^{-1} \boldsymbol{\beta} + \sigma^{-2} X_i^T Y_i), K)$$

where:

$$K = ((X_i^T X_i)^{-1} \boldsymbol{\Sigma}^{-1} + \sigma^{-2} (X_i^T X_i)^{-1})^{-1}$$

$$\propto \exp\left\{-\frac{1}{2}((\sigma_i^2(X_i^T X_i)^{-1}) + \Sigma^{-1})^{-1}\right\}((X_i^T X_i)^{-1}\Sigma^{-1}\beta + I\sigma_i^{-2}X_i^T Y_{it}))^T((\sigma_i^2(X_i^T X_i)^{-1} + \Sigma^{-1})((X_i^T X_i)^{-1}\Sigma^{-1}\beta + I\sigma_i^{-2}X_i^T Y_{it}))\}$$

2. For $\pi(\sigma^2|.)$:

$$\begin{aligned}\pi(\sigma^2|.) &= \propto f(\mathbf{Y}|\boldsymbol{\beta}_i, \sigma^2) \cdot \pi(\sigma^2) \\ &\propto \left(\prod_{i=1}^n \prod_{t=1}^{t_i} \sigma^{-1} \exp\left\{-\frac{(Y_{i,t} - \mu_{i,t})^2}{2\sigma^2}\right\} \right) \frac{1}{\sigma^2} \\ &\propto (\sigma^2)^{-1 - \sum t_i} \prod_{i=1}^n \prod_{t=1}^{t_i} \exp\left\{-\frac{(Y_{i,t} - \mu_{i,t})^2}{2\sigma^2}\right\} \\ &\propto \sigma^{-2 - \sum t_i} \exp\left\{-\frac{1}{2} \sum_{i=1}^n \sum_{t=1}^{t_i} (Y_{i,t} - \mu_{i,t})^2 \sigma^{-2}\right\}\end{aligned}$$

where,

$$\sigma^2 \sim \text{InvGamma}\left(\frac{\sum t_i}{2}, \frac{SSR}{2}\right)$$

$$SSR = \sum_{i=1}^n \sum_{t=1}^{t_i} (Y_{it} - X_i \beta_i)^T (Y_{it} - X_i \beta_i)$$

3. $\Sigma^{-1}|.:$

$$\begin{aligned}\pi(\Sigma^{-1}|.) &= \prod_{i=1}^n \pi(Y_{it}|\beta_i, \beta, \Sigma^{-1}, \sigma^2) \cdot \pi(\beta_i|\beta, \Sigma^{-1}) \cdot \pi(\Sigma^{-1}) \\ &\propto \Sigma^{-n} \exp\left\{-\frac{1}{2} \sum_{i=1}^n (\beta_i - \beta)^T \Sigma^{-1} (\beta_i - \beta)\right\} \cdot |\Sigma|^{-(d+1)} \exp\left\{-\frac{1}{2} \Sigma^{-1}\right\} \\ &\propto \Sigma^{-(n/2+d+1)} \exp\left\{-\frac{1}{2} \left(\sum_{i=1}^n (\beta_i - \beta)^T (\beta_i - \beta) + 1\right) n \Sigma^{-1}\right\} \\ \Sigma^{-1} &\sim \text{InvWhishart}\left(\frac{n}{2}, nSSR_{\beta_i}\right), \text{ where } SSR_{\beta_i} = \sum_{i=1}^n ((X_i^T X_i)^{-1} \beta_i - (X_i^T X_i)^{-1} \beta)^2\end{aligned}$$

4. $\beta|.:$

$$\begin{aligned}\pi(\beta|.) &= \pi(Y_{it}|.) \cdot \pi(\beta_i|.) \cdot \pi(\beta) \propto \pi(\beta_i|.) \\ &\propto \exp\left\{\frac{1}{2} \sum_{i=1}^n ((X_i^T X_i)^{-1} (\beta_i - \beta))^T ((X_i^T X_i)^{-1} (\beta_i - \beta)) ((X_i^T X_i)^{-1} \Sigma^{-1})\right\} \\ \beta &\sim N(\hat{\beta}_i, \Sigma^{-1}((X_i^T X_i)^{-1})), \text{ where } \hat{\beta} = (X_i^T X_i)^{-1} X_i^T Y_i\end{aligned}$$

Or, according to the Central Limit Theorem,

$$\frac{\beta_i - \beta}{\sqrt{\Sigma^{-1}/n}}, \quad \beta = \bar{\beta}_i \text{ for } i = 1, 2, \dots, n$$