

Posterior Derivation

For each hurricane i and k_i 's time points:

$$Y_i(t+6) = \beta_{0i} + \beta_{ij}Y_i(t) + \beta_x\Delta_{i1}(t) + \beta_{ii}\Delta_{i2}(t) + \beta_{4i}\Delta_{i3}(t) + \varepsilon_i(t)$$

$$Y_i(t+6) = x_i(t) \cdot \beta_i + \varepsilon_i(t), \text{ where } \beta_i = (\beta_{0i}, \beta_{1i}, \dots, \beta_{4i}) \sim N_5(\mu, \Sigma), \varepsilon_i(t) \sim N(0, \sigma^2)$$

$$Y_i | X_i \sim N_{k_i}(x_i\beta_i, \sigma^2 I_{k_i})$$

$$f(y_i | \beta_i, \nabla^2) = [(2\pi)^{k_i} \cdot \det(\sigma^2 I_{k_i})]^{-\frac{1}{2}} \cdot \exp\left\{-\frac{1}{2}(y_i - x_i\beta_i)^\top \cdot (\sigma^2 I_{k_i})^{-1} (y_i - x_i\beta_i)\right\}$$

Thus we can derive the Likelihood:

$$\begin{aligned} f(y | B, \sigma^2) &= \prod_{i=1}^n f(y_i | \beta_i, \sigma^2) \\ &= \prod_{i=1}^n \left([(2\pi)^{k_i} \cdot \det(\sigma^2 I_{k_i})]^{-\frac{1}{2}} \cdot \exp\left\{-\frac{1}{2}(y_i - x_i\beta_i)^\top \cdot (\sigma^2 I_{k_i})^{-1} (y_i - x_i\beta_i)\right\} \right) \end{aligned}$$

We have the Priors below:

$$\beta_i = (\beta_{0i}, \beta_{1i}, \dots, \beta_{4i}) \sim N_5(\mu, \Sigma)$$

$$B = (\beta_1^\top, \beta_2^\top, \dots, \beta_n^\top)^\top, \text{ assume } \beta_1, \beta_2, \dots, \beta_n \text{ are independent,}$$

$$\pi(B | \mu, \Sigma) = \prod_{i=1}^n f(\beta_i) = (2\pi)^{-5n/2} \cdot \det(\Sigma)^{-n/2} \cdot \exp\left\{-\frac{1}{2} \sum_i [(\beta_i - \mu)^\top \cdot (\Sigma)^{-1} \cdot (\beta_i - \mu)]\right\}$$

$$\pi(\sigma^2) \propto \frac{1}{\sigma^2}, \pi(\mu) \propto 1, \pi(\Sigma^{-1}) \propto |\Sigma|^{-(d+1)} \cdot \exp\left(-\frac{1}{2}\Sigma^{-1}\right)$$

We can then derive the Posterior:

$$g(B, \sigma^2 | y) \propto g(y | B, \sigma^2) \cdot \pi(B | \mu, \Sigma) \cdot \pi(\sigma^2) \cdot \pi(\mu) \cdot \pi(\Sigma^{-1})$$

$$\begin{aligned} \pi(\sigma^2 | \cdot) &\propto \prod_{i=1}^n \det(\sigma^2 I_{k_i})^{-\frac{1}{2}} \cdot \exp\left\{-\frac{1}{2} \sum_i [(y_i - x_i\beta_i)^\top (\sigma^2 I_{k_i})^{-1} (y_i - x_i\beta_i)]\right\} \cdot \sigma^{-2} \\ &= (\sigma^2)^{-\frac{1}{2} \sum_i k_i} \cdot \exp\left\{-\frac{1}{2\sigma^2} \sum_i [(y_i - x_i\beta_i)^\top \cdot (y_i - x_i\beta_i)]\right\} \cdot \sigma^{-2} \\ &= (\sigma^2)^{-1 - \frac{1}{2} \sum_i k_i} \cdot \exp\left\{-\frac{1}{2\sigma^2} \sum_i \sum_{ti} (y_{i,t} - x_{i,t} \cdot \beta_i)^2\right\}, \text{ assume } w = (\sigma^2)^{-1} \\ &= w \left(1 + \frac{1}{2} \sum_i k_i\right) \cdot \exp\left\{-w \cdot \frac{1}{2} \cdot \sum_i \sum_{ti} (y_{i,t} - x_{i,t} \cdot \beta_i)^2\right\} \end{aligned}$$

Therefore, $w \sim \text{Gamma}\left(\frac{1}{2} \sum_i k_i + 2, \frac{1}{2} \sum_i \sum_{ti} (y_{i,t} - x_{i,t} \cdot \beta_i)^2\right)$.

$$\begin{aligned}
\pi(\Sigma^{-1}) &\propto \det(\Sigma)^{-n/2} \cdot \exp \left\{ -\frac{1}{2} \Sigma_i (\beta_i - \mu)^\top \Sigma^{-1} (\beta_i - \mu) \right\} \cdot \det(\Sigma)^{-(d+1)} \cdot \exp \left\{ -\frac{1}{2} \Sigma^{-1} \right\} \\
&= \det(\Sigma)^{-(n|2+d+1)} \cdot \exp \left\{ -\frac{1}{2} \left[\Sigma^{-1} + \Sigma_i (\beta_i - \mu)^\top \Sigma^{-1} (\beta_i - \mu) \right] \right\} \\
&\propto \det(\Sigma)^{-(n+2d+2)/2} \cdot \exp \left\{ -\frac{1}{2} \text{tr} \left[\Sigma^{-1} \cdot \left(I + \Sigma_i (\beta_i - \mu) (\beta_i - \mu)^\top \right) \right] \right\} \\
&\propto \det(\Sigma)^{-(n+2d+2)/2} \cdot \exp \left\{ -\frac{1}{2} \text{tr} \left[\Sigma^{-1} \cdot \left(I + \Sigma_i (\beta_i - \mu) (\beta_i - \mu)^\top \right) \right] \right\}
\end{aligned}$$

Thus $\Sigma^{-1} \sim \text{Wishart} \left(n + 3d + 3, I + \Sigma_i (\beta_i - \mu)^\top (\beta_i - \mu) \right)$

$$\begin{aligned}
\pi(\mu) &\propto \exp \left\{ -\frac{1}{2} \Sigma_i \left[(\beta_i - \mu)^\top \Sigma^{-1} (\beta_i - \mu) \right] \right\} \\
&= \exp \left\{ -\frac{1}{2} \Sigma_i \left(\beta_i^\top \Sigma^{-1} \beta_i + \mu^\top \Sigma^{-1} \mu - 2 \beta_i^\top \Sigma^{-1} \mu \right) \right\} \\
&= \exp \left\{ -\frac{1}{2} \left(\Sigma_i \beta_i^\top \Sigma^{-1} \beta_i + \mu^\top n \Sigma^{-1} \mu - 2 \Sigma_i \beta_i^\top \Sigma^{-1} \mu \right) \right\} \\
&= \exp \left\{ -\frac{1}{2} \left(\mu^\top n \Sigma^{-1} \mu - 2 \Sigma_i \beta_i^\top \Sigma^{-1} \mu + \Sigma_i - \beta_i^\top \Sigma^{-1} \beta_i \right) \right\} \\
&= \exp \left\{ -\frac{1}{2} \left(\mu^\top \underbrace{n \Sigma^{-1}}_M \mu - 2 \mu^\top \underbrace{\Sigma_i \Sigma^{-1} \beta_i + \Sigma_i \beta_i^\top \Sigma^{-1}}_N \right) \right\} \\
&= \exp \left\{ -\frac{1}{2} \left[(\mu - M^{-1} N)^\top M (\mu - M^{-1} N) \right] \right\}
\end{aligned}$$

$$\begin{aligned}
\pi(B) &\propto \exp \left\{ -\frac{1}{2} \Sigma_i \left[(y_i - x_i \beta_i)^\top (\sigma^2 I_{ki})^{-1} (y_i - x_i \beta_i) \right] \right\} \cdot \exp \left\{ -\frac{1}{2} \Sigma_i \left[(\beta_i - \mu)^\top \cdot (\Sigma)^{-1} \cdot (\beta_i - \mu) \right] \right\} \\
&= \exp \left\{ -\frac{1}{2} \Sigma_i \left[(y_i - x_i \beta_i)^\top (\sigma^2 I_{ki})^{-1} (y_i - x_i \beta_i) + (\beta_i - \mu)^\top \cdot \Sigma^{-1} (\beta_i - \mu) \right] \right\} \\
&= \exp \left\{ y_i^\top \sigma^{-2} I_{ki} y_i^\top + \beta_i^\top x_i^\top \sigma^{-2} I_{ki} x_i \beta_i - 2 y_i^\top \sigma^{-2} I_{ki} x_i \beta_i + \beta_i^\top \Sigma^{-1} \beta_i + \mu^\top \Sigma^{-1} \mu - 2 \mu^\top \Sigma^{-1} \beta_i \right\} \\
&= \exp \left\{ y_i^\top \sigma^{-2} I_{ki} y_i + \mu^\top \Sigma^{-1} \mu + \beta_i^\top (\Sigma^{-1} + x_i^\top \sigma^{-2} I_{ki} x_i) \beta_i - 2 (y_i^\top \sigma^{-2} I_{ki} x_i + \mu^\top \Sigma^{-1}) \beta_i \right\}
\end{aligned}$$

We can define the following terms:

$$\begin{aligned}
R &= y_i^\top \sigma^{-2} I_{ki} y_i + \mu^\top \Sigma^{-1} \mu \\
V &= \Sigma^{-1} + x_i^\top \sigma^{-2} I_{ki} x_i \\
M &= \sigma^{-2} x_i^\top y_i + \Sigma^{-1} \mu
\end{aligned}$$

Thus, $\pi(B | \dots) \propto (\beta_i - V^{-1} M)^\top \cdot V \cdot (\beta_i - V^{-1} M) \sim N(V^{-1} M, V^{-1})$