

# Posteria distribution deriviation

Qetsiyah Wang and Wenhao Gou

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## 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 dont 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  $\sigma^2$ , independent across  $t$

## 2 Distributon and priors:

Marginal distributions for  $Y_{i,t+6}$ :

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

Priors:

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

### 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:

Suppose for hurricane  $i$ , we have  $t_i$  observations which can be used to build model, denote following matrixs for response and predictors for hurricane  $i$ :

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

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

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

For the exponential term:

$$\begin{aligned} &(\mathbf{Y}_i - \mathbf{X}_i \boldsymbol{\beta}_i)^T (\sigma^{-2} \mathbf{I}_{t_i \times t_i}) (\mathbf{Y}_i - \mathbf{X}_i \boldsymbol{\beta}_i) + (\boldsymbol{\beta}_i - \boldsymbol{\beta})^T \boldsymbol{\Sigma}_{8 \times 8}^{-1} (\boldsymbol{\beta}_i - \boldsymbol{\beta}) \\ &= \mathbf{Y}_i^T \sigma^{-2} \mathbf{I} \mathbf{Y}_i^T + \boldsymbol{\beta}_i^T \mathbf{X}_i^T \sigma^{-2} \mathbf{I} \mathbf{X}_i \boldsymbol{\beta}_i - 2 \mathbf{Y}_i^T \sigma^{-2} \mathbf{I} \mathbf{X}_i \boldsymbol{\beta}_i \\ &\quad + \boldsymbol{\beta}_i^T \boldsymbol{\Sigma}^{-1} \boldsymbol{\beta}_i + \boldsymbol{\beta}^T \boldsymbol{\Sigma}^{-1} \boldsymbol{\beta} - 2 \boldsymbol{\beta}^T \boldsymbol{\Sigma}^{-1} \boldsymbol{\beta}_i \\ &= \mathbf{Y}_i^T \sigma^{-2} \mathbf{I} \mathbf{Y}_i^T + \boldsymbol{\beta}^T \boldsymbol{\Sigma}^{-1} \boldsymbol{\beta} + \boldsymbol{\beta}_i^T (\boldsymbol{\Sigma}^{-1} + \mathbf{X}_i^T \sigma^{-2} \mathbf{I} \mathbf{X}_i) \boldsymbol{\beta}_i \\ &\quad - 2(\mathbf{Y}_i^T \sigma^{-2} \mathbf{I} \mathbf{X}_i + \boldsymbol{\beta}^T \boldsymbol{\Sigma}^{-1}) \boldsymbol{\beta}_i \\ &= \mathbf{R} + \boldsymbol{\beta}_i^T \mathbf{V} \boldsymbol{\beta}_i - 2 \mathbf{M} \boldsymbol{\beta}_i \end{aligned}$$

Where:

$$\begin{aligned}\mathbf{R} &= \mathbf{Y}_i^T \sigma^{-2} \mathbf{I} \mathbf{Y}_i^T + \boldsymbol{\beta}^T \boldsymbol{\Sigma}^{-1} \boldsymbol{\beta} \\ \mathbf{V} &= \boldsymbol{\Sigma}^{-1} + \sigma^{-2} \mathbf{X}_i^T \mathbf{X}_i \\ \mathbf{M} &= \sigma^{-2} \mathbf{Y}_i^T \mathbf{X}_i + \boldsymbol{\beta}^T \boldsymbol{\Sigma}^{-1}\end{aligned}$$

Then, the exponential term can be reduced to:

$$(\boldsymbol{\beta}_i - \mathbf{V}^{-1} \mathbf{M})^T \mathbf{V} (\boldsymbol{\beta}_i - \mathbf{V}^{-1} \mathbf{M}) - \mathbf{M}^T \mathbf{V}^{-1} \mathbf{M}^T + \mathbf{R}$$

We can ignore the latter 2 term as it is not related to  $\boldsymbol{\beta}_i$ . That indicate:

$$\pi(\boldsymbol{\beta}_i | \cdot) \sim N(\mathbf{V}^{-1} \mathbf{M}, \mathbf{V}^{-1})$$

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

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

So:

$$\sigma^2 \sim \text{InvGamma}\left(\frac{1}{2} \sum_{i=1}^n t_i, \frac{1}{2} \sum_{i=1}^n \sum_{t=1}^{t_i} (Y_{i,t} - \mu_{i,t})^2\right)$$

3. For  $\pi(\boldsymbol{\Sigma}^{-1} | \cdot)$ :

$$\begin{aligned}\pi(\boldsymbol{\Sigma}^{-1} | \cdot) &\propto f(\boldsymbol{\beta}_i | \boldsymbol{\beta}, \boldsymbol{\Sigma}^{-1}) f(\boldsymbol{\Sigma}^{-1}) \\ &\propto \left( \prod_{i=1}^n \boldsymbol{\Sigma}^{-\frac{1}{2}} \exp\left\{-\frac{1}{2} (\boldsymbol{\beta}_i - \boldsymbol{\beta})^T \boldsymbol{\Sigma}^{-1} (\boldsymbol{\beta}_i - \boldsymbol{\beta})\right\} \right) |\boldsymbol{\Sigma}|^{-(d-1)/2} \exp\left\{-\frac{1}{2} \boldsymbol{\Sigma}^{-1}\right\} \\ &\propto |\boldsymbol{\Sigma}|^{-(n+d+1)/2} \exp\left\{-\frac{1}{2} \text{tr}(\boldsymbol{\Sigma}^{-1}) - \frac{1}{2} \sum_{i=1}^n (\boldsymbol{\beta}_i - \boldsymbol{\beta})^T \boldsymbol{\Sigma}^{-1} (\boldsymbol{\beta}_i - \boldsymbol{\beta})\right\} \\ &\propto |\boldsymbol{\Sigma}|^{-(n+d+1)/2} \exp\left\{-\frac{1}{2} \text{tr}\left(\boldsymbol{\Sigma}^{-1} (\mathbf{I} + \sum_{i=1}^n (\boldsymbol{\beta}_i - \boldsymbol{\beta})(\boldsymbol{\beta}_i - \boldsymbol{\beta})^T)\right)\right\}\end{aligned}$$

That indicate:

$$\boldsymbol{\Sigma}^{-1} \sim \text{InvWhishart}\left(n, \mathbf{I} + \sum_{i=1}^n (\boldsymbol{\beta}_i - \boldsymbol{\beta})(\boldsymbol{\beta}_i - \boldsymbol{\beta})^T\right)$$

4. For  $\pi(\boldsymbol{\beta}|.)$ :

$$\begin{aligned}
\pi(\boldsymbol{\beta}|.) &\propto f(\boldsymbol{\beta}_i|\boldsymbol{\beta}, \boldsymbol{\Sigma}^{-1})f(\boldsymbol{\beta}) \\
&\propto \left( \prod_{i=1}^n \exp\left\{-\frac{1}{2}(\boldsymbol{\beta}_i - \boldsymbol{\beta})^T \boldsymbol{\Sigma}^{-1}(\boldsymbol{\beta}_i - \boldsymbol{\beta})\right\} \right) \\
&\propto \exp\left\{-\frac{1}{2}\left(\sum_{i=1}^n (\boldsymbol{\beta}_i - \boldsymbol{\beta})^T \boldsymbol{\Sigma}^{-1}(\boldsymbol{\beta}_i - \boldsymbol{\beta})\right)\right\} \\
&\propto \exp\left\{-\frac{1}{2}\left(\sum_{i=1}^n \boldsymbol{\beta}_i^T \boldsymbol{\Sigma}^{-1} \boldsymbol{\beta}_i + \boldsymbol{\beta}^T n \boldsymbol{\Sigma}^{-1} \boldsymbol{\beta} - \sum_{i=1}^n 2\boldsymbol{\beta}_i^T \boldsymbol{\Sigma}^{-1} \boldsymbol{\beta}\right)\right\}
\end{aligned}$$

For the exponential term, if we set:

$$\begin{aligned}
\mathbf{V} &= n\boldsymbol{\Sigma}^{-1} \\
\mathbf{R} &= \sum_{i=1}^n \boldsymbol{\beta}_i^T \boldsymbol{\Sigma}^{-1} \boldsymbol{\beta}_i \\
\mathbf{M} &= \sum_{i=1}^n \left( \boldsymbol{\Sigma}^{-1} \boldsymbol{\beta}_i \right)
\end{aligned}$$

Then, use the same technique when generating  $\boldsymbol{\beta}_i$

$$R + \boldsymbol{\beta} \mathbf{V} \boldsymbol{\beta} - 2\mathbf{M} \boldsymbol{\beta} \propto (\boldsymbol{\beta} - \mathbf{V}^{-1} \mathbf{M})^T \mathbf{V}^{-1} (\boldsymbol{\beta} - \mathbf{V}^{-1} \mathbf{M})$$

(NOTE: This is the same as using OLS to estimate  $\boldsymbol{\beta}$  using all  $\boldsymbol{\beta}_i$ )

That indicate:

$$\boldsymbol{\beta} \sim N\left(\frac{1}{n} \sum_{i=1}^n \boldsymbol{\beta}_i, \frac{1}{n} \boldsymbol{\Sigma}\right)$$