# P8160 - Bayesian Modeling of Hurricane Trajectories

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# MCMC for Hierarchical Bayesian Model:Data Partition

#### **Data Partition**

- ► For each hurricane, 80% of records were randomly assigned to the training set and the remaining 20% were assigned to testing set.
- Hurricanes with less than 7 records were removed: at least 5 observations are included in the training set and 1 observation is included in the testing set.

#### **Distribution Derivation:**

- ► Gibbs sampler is used to generate random variables from given distribution:
- Let  $\Theta = (\mathbf{B}^T, \boldsymbol{\beta}^T, \boldsymbol{\sigma}^2, \boldsymbol{\Sigma})$ , the posterior distribution can be written as:

$$P(\Theta \mid Y) \propto f(Y|\Theta)P(\Theta)$$
  
=  $f(Y \mid \boldsymbol{B}, \beta, \sigma^2, \boldsymbol{\Sigma})f(\boldsymbol{B} \mid \beta, \boldsymbol{\Sigma})P(\beta)P(\sigma^2)P(\boldsymbol{\Sigma}^{-1})$ 

### Conditional Distribution of $\Theta$ :

▶  $Y_i \sim MVN(X_i\beta_i^T, \sigma^2 I_{n_i})$ , where  $n_i$  is the number of observation of the  $i^{th}$  hurricane.

$$f(Y \mid \boldsymbol{B}, \beta, \sigma^2, \boldsymbol{\Sigma}) = \prod_{i=1}^{N} f(Y_i \mid B, \beta, \boldsymbol{\Sigma}, \sigma^2)$$

$$= \prod_{i=1}^{N} (2\pi)^{-\frac{n_i}{2}} \left| \sigma^2 I_{n_i} \right|^{-\frac{1}{2}} \exp(-\frac{1}{2} (Y_i - X_i \beta_i^T)^T (\sigma^2 I_{n_i})^{-1}$$

$$\triangleright$$
  $\beta_i \sim \mathsf{MVN}(\mu, \Sigma)$ :

$$f(B|\beta, \Sigma) = \prod_{i=1}^{N} (2\pi)^{-\frac{5}{2}} |\sigma|^{-\frac{1}{2}} \exp\left(-\frac{1}{2}(\beta_i - \mu)^T \Sigma^{-1}(\beta_i - \mu)\right)$$

## **Conditional Distribution of ⊖**:

▶ the posterior distribution of Θ, where  $A = Σ^{-1}$ :

$$P(\Theta \mid Y) \propto \sigma^{-\sum_{i=1}^{N} n_i - 2} |A|^{d + \frac{N}{2} + 1}$$

$$\exp \left[ -\frac{1}{2} \sum_{i=1}^{N} \left[ (Y_i - X_i \beta_i^T)^T (\sigma^2 I_{n_i})^{-1} (Y_i - X_i \beta_i^T) + (\beta_i - \mu)^T (\gamma_i - X_i \beta_i^T) \right] + (\beta_i - \mu)^T (\gamma_i - X_i \beta_i^T) + (\beta_i$$

## Conditional Distribution of each parameter:

- $\beta_{i} \sim MVN(V^{-1}M, V^{-1}) \text{ where, } V = \Sigma^{-1} + X_{i}^{T} \sigma^{-2} I_{ni} X_{i}, \\ R = Y_{i}^{T} \sigma^{-2} I_{ni} Y_{i} + \mu^{T} \Sigma^{-1} \mu, M = Y_{i}^{T} \sigma^{-2} I_{ni} X_{i} + \mu^{T} \Sigma^{-1}$
- $μ \sim MVN(V^{-1}M, V^{-1}), V = NΣ^{-1}, R = \sum_{i=1}^{N} β_i^T Σ^{-1} β_i, M = \sum_{i=1}^{N} Σ^{-1} β_i$
- $W \sim \text{inverse Gamma}(\frac{\sum_{i=1}^N n_i}{2}, \frac{1}{2}\sum_{i=1}^N \sum_{t=1}^{n_i} (y_{it} x_{it}\beta_i^T)^2)$ ,  $W = \sigma^2$
- ►  $A \sim \text{Wishart} \left(3d + N + 3, \left(I + \sum_{i=1}^{N} (\beta_i \mu)(\beta_i \mu)^T\right)^{-1}\right),$  $A = \Sigma^{-1}$