

# Baysian modeling of hurricane trajectories

## P8160 Group Project 3 Baysian modeling of hurricane trajectories

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# Content

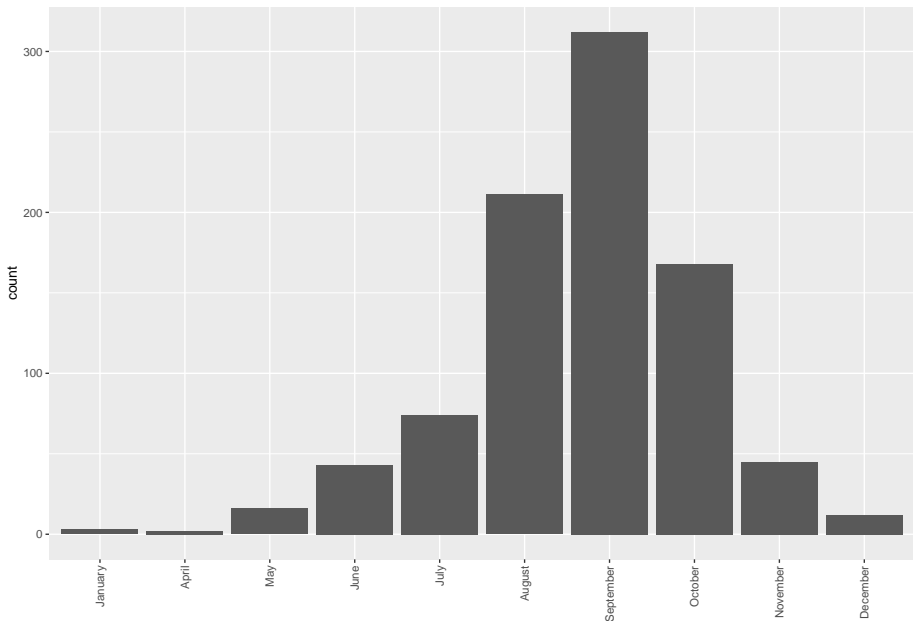
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# Introduction

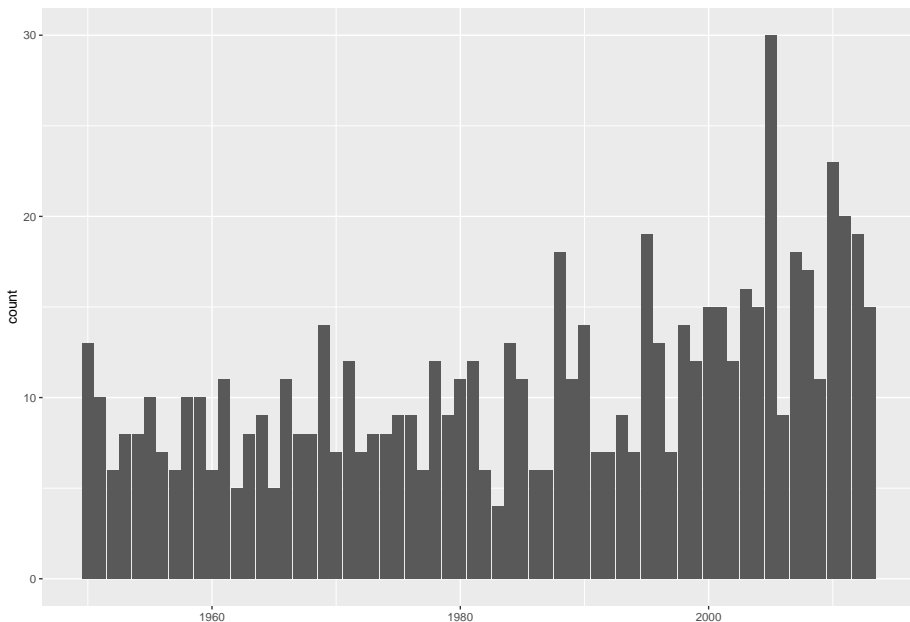
- Hurricanes cause fatalities and property damage
- there is a growing need to accurately predict hurricane behavior, including location and speed
- This project aims to forecast wind speeds by modeling hurricane trajectories using a Hierarchical Bayesian Model.

- Hurrican703 dataset: 22038 observations  $\times$  8 variables
  - 702 hurricanes in the North Atlantic area since 1950

# EDA-Count of Hurricanes in each Month

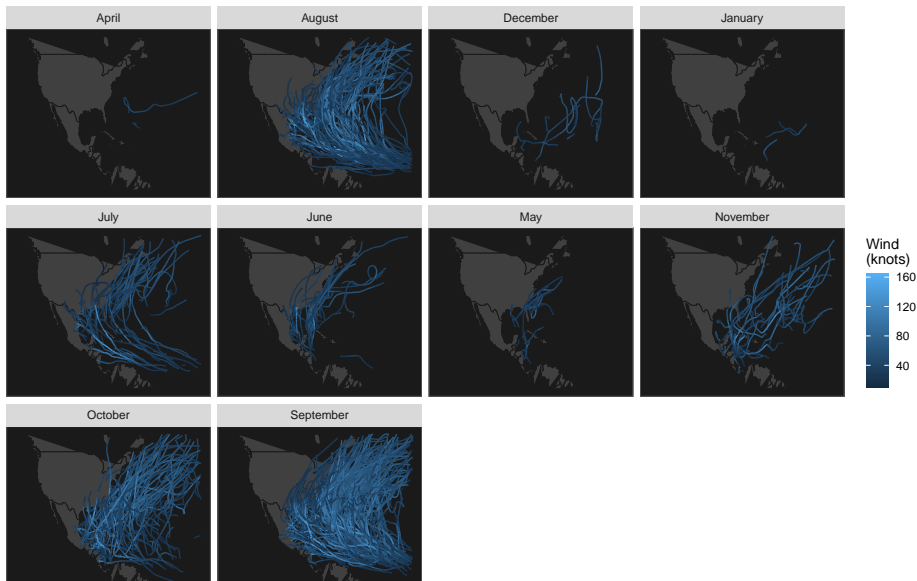


# EDA-Count of Hurricanes in each Year



# Show hurricane tracks by month

Atlantic named Windstorm Trajectories by Month ( 1950 – 2013 )



# Bayesian Model

The suggested Bayesian model is

$$Y_i(t+6) = \beta_{0,i} + \beta_{1,i} Y_i(t) + \beta_{2,i} \Delta_{i,1}(t) + \beta_{3,i} \Delta_{i,2}(t) + \beta_{4,i} \Delta_{i,3}(t) + \mathbf{X}_i \gamma + \epsilon_i(t)$$

- where  $Y_i(t)$  the wind speed at time  $t$  (i.e. 6 hours earlier),  $\Delta_{i,1}(t)$ ,  $\Delta_{i,2}(t)$  and  $\Delta_{i,3}(t)$  are the changes of latitude, longitude and wind speed between  $t$  and  $t - 6$ , and  $\epsilon_{i,t}$  follows a normal distributions with mean zero and variance  $\sigma^2$ , independent across  $t$ .
- $\beta_i = (\beta_{0,i}, \beta_{1,i}, \dots, \beta_{5,i})$ , we assume that  $\beta_i \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ , where  $d$  is dimension of  $\beta_i$ .



$$P(\boldsymbol{\mu}) = \frac{1}{\sqrt{2\pi}|\mathbf{V}|^{\frac{1}{2}}} \exp\left\{-\frac{1}{2}\boldsymbol{\mu}^\top \mathbf{V}^{-1}\boldsymbol{\mu}\right\} \propto |\mathbf{V}|^{-\frac{1}{2}} \exp\left\{-\frac{1}{2}\boldsymbol{\mu}^\top \mathbf{V}^{-1}\boldsymbol{\mu}\right\} \quad (2)$$

$$P(\Sigma^{-1}) \propto |\Sigma|^{-\frac{(\nu+d+1)}{2}} \exp\left(-\frac{1}{2}\text{tr}(S\Sigma^{-1})\right) \quad (3)$$

$$P(\gamma) \propto \exp\left(-\frac{\gamma^2}{2 * (0.05)^2}\right) = e^{-200\gamma^2} \quad (4)$$

$$P(\sigma) = \frac{2\alpha}{\pi + \alpha^2} \propto \frac{1}{\sigma^2 + \alpha^2} \quad (5)$$

# Posterior

Let  $\mathbf{B} = (\beta_1^\top, \dots, \beta_n^\top)^\top$ , derive the posterior distribution of the parameters  $\Theta = (\mathbf{B}^\top, \boldsymbol{\mu}^\top, \sigma^2, \boldsymbol{\Sigma}, \gamma)$ .

Let

$$\mathbf{Z}_i(t)\beta_i^\top = \beta_{0,i} + \beta_{1,i}Y_i(t) + \beta_{2,i}\Delta_{i,1}(t) + \beta_{3,i}\Delta_{i,2}(t) + \beta_{4,i}\Delta_{i,3}(t)$$

We can find that

$$\mathbf{Y}_i \sim MVN(\mathbf{Z}_i\beta_i, \sigma^2 I) \quad (6)$$

The likelihood for our data is

$$\begin{aligned} L(\mathbf{Y}_i \mid \mathbf{B}_i, \sigma^2) &= \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma}} \exp\left\{-\frac{1}{2}(\mathbf{y}_i - \mathbf{Z}_i\beta_i - \mathbf{X}_i\gamma_i)^\top (\sigma^2 I)^{-1} (\mathbf{y}_i - \mathbf{Z}_i\beta_i - \mathbf{X}_i\gamma_i)\right\} \\ &\propto (\sigma^{-\frac{N}{2}}) \prod_{i=1}^n \exp\left\{-\frac{1}{2}(\mathbf{Y}_i - \mathbf{Z}_i\beta_i - \mathbf{X}_i\gamma_i)^\top (\sigma^2 I)^{-1} (\mathbf{Y}_i - \mathbf{Z}_i\beta_i - \mathbf{X}_i\gamma_i)\right\} \end{aligned} \quad (7)$$

$$\begin{aligned} P(\Theta|Y) &= P(B, \mu, \sigma^2, A, \gamma|Y) \\ &\propto L(Y|B, \sigma^2) L(B|\mu, \Sigma) p(\mu) p(\sigma) p(A) p(\gamma) \\ &\propto \frac{1}{\sigma^N (\sigma^2 + 10^2)} \prod_{i=1}^n \exp \left\{ -\frac{1}{2} (\mathbf{Y}_i - \mathbf{Z}_i \beta_i - \mathbf{X}_i \gamma_i)^\top (\sigma^2 I)^{-1} (\mathbf{Y}_i - \right. \\ &\quad \times \exp \left\{ -\frac{1}{2} \sum_i^n (\beta_i - \mu)^\top A (\beta_i - \mu) \right\} |A|^{\frac{N+d+6}{2}} \exp \left\{ -\frac{1}{2} \text{tr}(SA) \right\} |\mathbf{V}|^{-\frac{1}{2}} \\ &\quad \left. \right\} \end{aligned} \tag{9}$$

# Conditional Distributions

Generate  $B_t$  from  $f(B_t, \sigma_{t-1}, \mu_{t-1}, \Sigma_{t-1}^{-1})$

$$\begin{aligned} f(B^\top | \sigma^2, \mu, \Sigma) &\propto \prod_{i=1}^n \exp\left\{-\frac{(Y_j - Z_j\beta_j - X_j\gamma)^\top (Y_j Z_j\beta_j - X_j\gamma) - (\beta_j - \mu)^\top \Sigma}{2\sigma^2}\right\} \\ &\propto \prod_{i=1}^n \exp\left(-\frac{1}{2}(\beta_j^\top \left(\frac{Z_j^\top Z_j}{\sigma^2} + A\right)\beta_j - 2\left(\frac{Y_j^\top Z_j - X_j^\top Z_j\gamma}{\sigma^2}\right)\right) \\ &\propto \prod_{i=1}^n \exp\left\{-\frac{1}{2}\left(\beta_j - \left(\frac{Z_j^\top Z_j}{\sigma^2} + A\right)^{-1}\left(\frac{Y_j^\top Z_j - X_j^\top Z_j\gamma}{\sigma^2}\right)\right)^\top \left(\frac{Z_j^\top Z_j}{\sigma^2} + A\right)^{-1}\right. \\ &\quad \left. \left(\frac{Y_j^\top Z_j - X_j^\top Z_j\gamma}{\sigma^2} + \mu^\top A\right)^\top, \frac{Z_j^\top Z_j}{\sigma^2} + A\right\} \end{aligned}$$

# MCMC Algorithm

$$f(\mathbf{B}|\mu^\top, \sigma^2, A, \gamma, Y^\top) \sim MVN_d((\frac{Z_j^\top Z_j}{\sigma^2} + A)^{-1}(\frac{Y_j^\top Z_j^\top - X_j^\top Z_j \gamma}{\sigma^2} + \mu^\top A)^\top, \frac{Z_j^\top Z_j}{\sigma^2} + A)$$

$$f(\mu_t|B^\top, \sigma^2, A, \gamma, Y^\top) \sim MVN_d((NA + \frac{1}{v})^{-1}(\sum_i^n \beta_j A)^\top, (NA + \frac{1}{v})^{-1})$$

$$f(\sigma|B^\top, \mu^\top, A, \gamma, Y^\top) \sim MVN_d((X_i^\top \sigma^{-2} I X_i + 400I)^{-1}(X_i^\top \sigma^{-2} I Y_i - X_i^\top \sigma^{-2} I Z_i \gamma), \sigma^2)$$

$$f(\mathbf{A}|\mathbf{B}^\top \sigma^2, \gamma, \mathbf{Y}^\top) \sim w^{-1}(\mathbf{S} + \sum_i^n (\beta_i - \mu)(\beta_i - \mu)^\top, n + v)$$

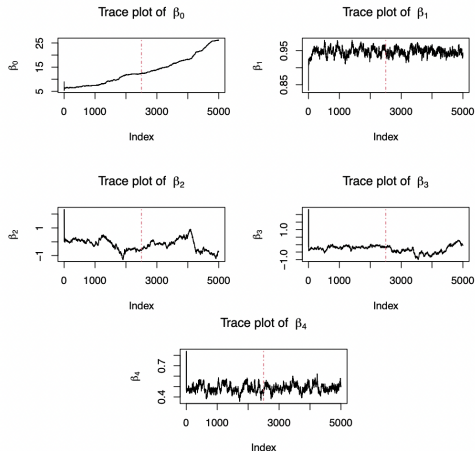
$$f(\gamma|B^\top, \mu^{top}, \sigma^2, A, Y^\top) \sim MVN((\frac{X_j^\top X_j}{\sigma^2} + 400I)^{-1}(\sum_i^n Y_j^\top X_j - \sum_i^n X_j Z_j \beta_j)^\top, \frac{X_j^\top X_j}{\sigma^2} + 400I)$$

# MCMC Results - Details

- 5000 iterations
- Estimates and inferences based on 5000 MCMC samples

# MCMC Results - Beta Plots 1

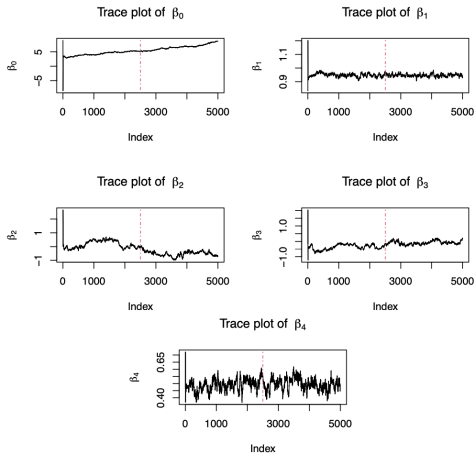
Beta plot



-Trace plots of variance parameters, based on 5000 MCMC sample.

# MCMC Results - Beta Plots 2

Beta plot

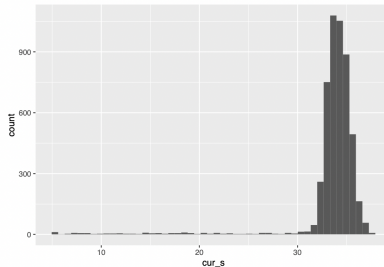
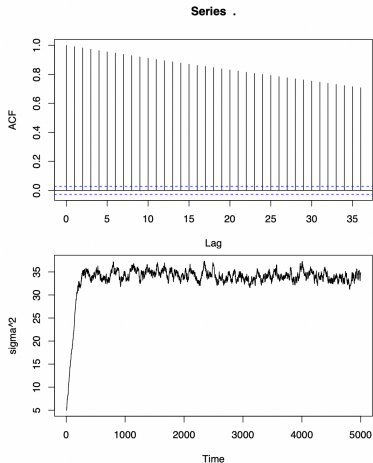


-Trace plots of variance parameters, based on 5000 MCMC sample.



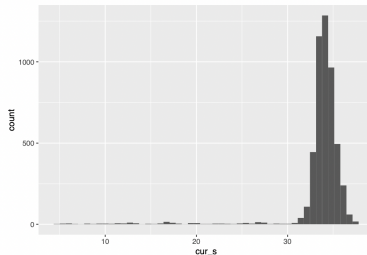
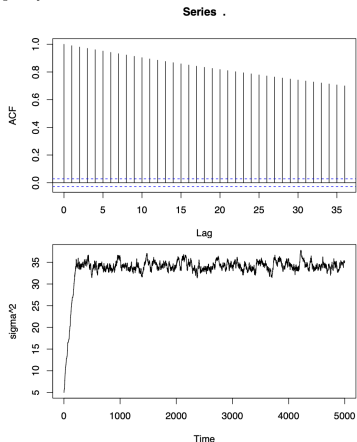
# MCMC Results - $\sigma^2$ Plots 1

$\sigma^2$  plot



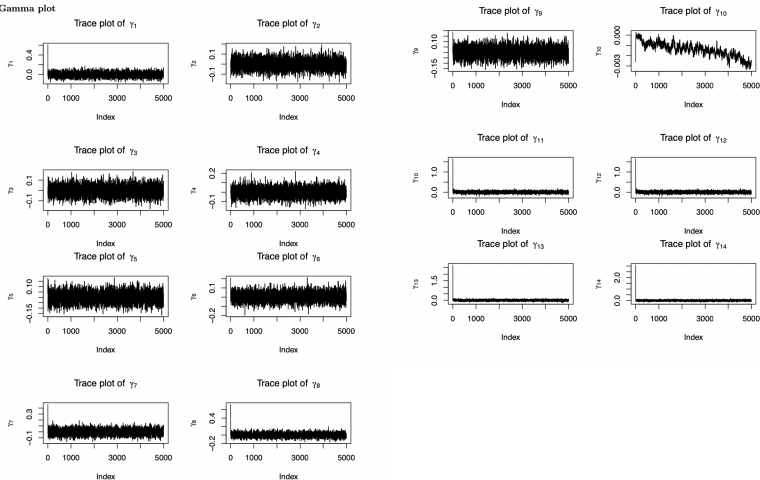
# MCMC Results - $\sigma^2$ Plots 2

$\sigma^2$  plot



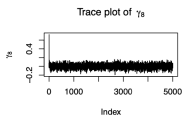
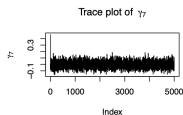
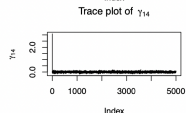
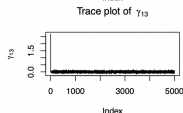
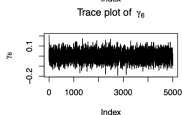
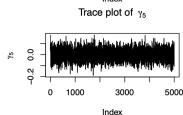
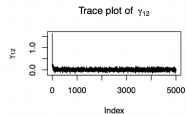
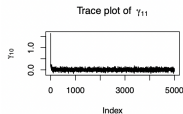
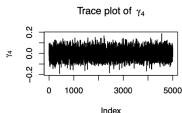
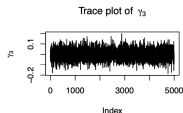
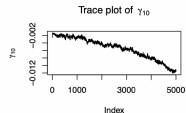
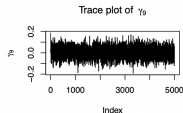
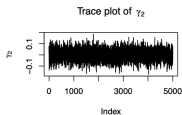
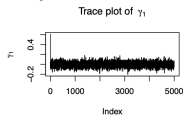
# MCMC Results - Gamma Plots 1

Gamma plot



# MCMC Results - Gamma Plots 2

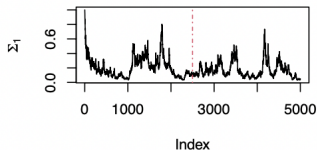
Gamma plot



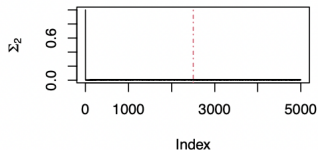
# MCMC Results - Sigma Inverse Plots 1

Sigma\_inverse plot

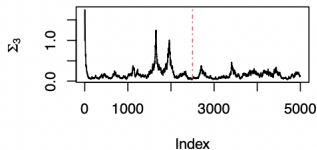
Trace plot of  $\Sigma_1$



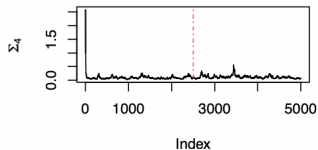
Trace plot of  $\Sigma_2$



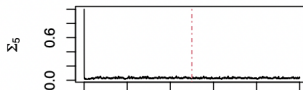
Trace plot of  $\Sigma_3$



Trace plot of  $\Sigma_4$



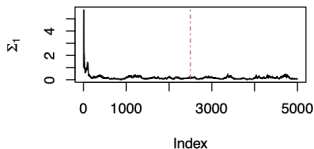
Trace plot of  $\Sigma_5$



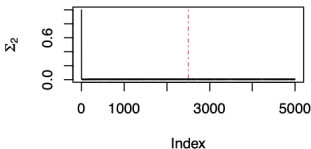
# MCMC Results - Sigma Inverse Plots 2

Sigma\_inverse plot

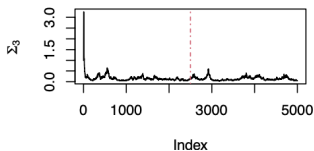
Trace plot of  $\Sigma_1$



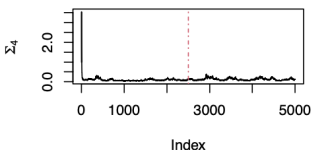
Trace plot of  $\Sigma_2$



Trace plot of  $\Sigma_3$



Trace plot of  $\Sigma_4$



Trace plot of  $\Sigma_5$

