# Baysian modeling of hurricane trajectories P8160 Group Project 3 Baysian modeling of hurricane trajectories

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#### Introduction

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- 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.

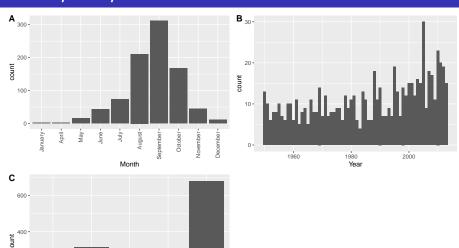
#### **Dataset**

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

## EDA-Count of Hurricanes in each Month/Year/Nature

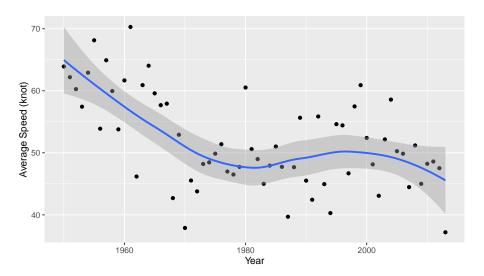
## **EDA-Count of Hurricanes in each Month/Year/Nature**



200 -

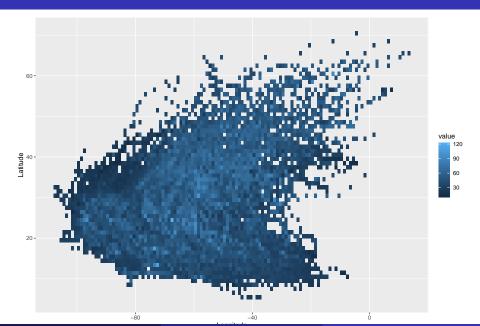
## EDA - Average Speed (knot) of Hurricanes in Each Year

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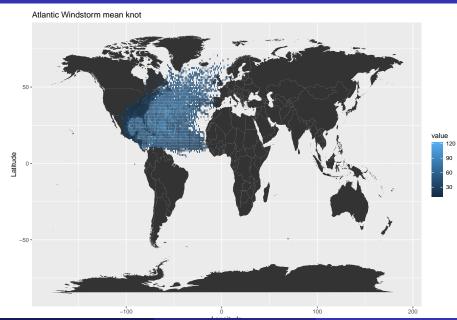
#### overview the hurrican data

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the hurrican data in the world map

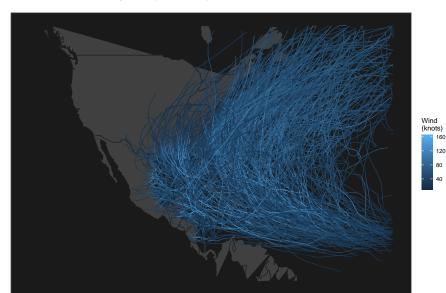
## the hurrican data in the world map



#### **Additional Plots**

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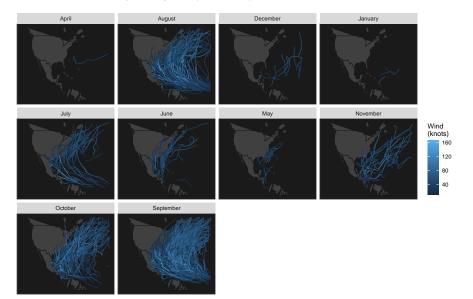
Atlantic named Windstorm Trajectories (1950 - 2013)



## Show hurricance tracks by month

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## **Bayesian Model Setting**

#### Model

The suggested Bayesian model is

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

- 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.
- $\beta_i = (\beta_{0,i}, \beta_{1,i}, ..., \beta_{5,i})$ , we assume that  $\beta_i \sim N(\mu, \Sigma_{d \times d})$ , where d is dimension of  $\beta_i$ .

## **Priors**

#### **Priors**

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

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

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

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

#### **Posterior**

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Let  $\mathbf{B} = (\beta_1^\top, ..., \beta_n^\top)^\top$ , 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

$$\mathbf{Y}_{i} \sim MVN(\mathbf{Z}_{i}\boldsymbol{\beta}_{i}, \sigma^{2}\boldsymbol{I})$$
 (6)

The likelihood for our data is

$$L(\mathbf{Y}_i \mid \mathbf{B}_i, \sigma^2) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi}\sigma} \exp\{-\frac{1}{2}(\mathbf{y}_i - \mathbf{Z}_i\beta_i - \mathbf{X}_i\gamma_i)^\top (\sigma^2 I)^{-1}(\mathbf{y}_i - \mathbf{Z}_i\beta_i - \mathbf{X}_i\gamma_i)^\top (\sigma^2 I)^\top (\sigma$$

′

#### **Joint Posrerior**

$$P(\Theta|Y) = P(B, \mu, \sigma^{2}, A, \gamma|Y)$$

$$\propto L(Y|B, \sigma^{2})L(B|\mu, \Sigma)p(\mu)p(\sigma)p(A)p(\gamma)$$

$$\propto \frac{1}{\sigma^{N}(\sigma^{2} + 10^{2})} \prod_{i=1}^{n} \exp\left\{-\frac{1}{2}(\mathbf{Y}_{i} - \mathbf{Z}_{i}\beta_{i} - \mathbf{X}_{i}\gamma_{i})^{\top}(\sigma^{2}I)^{-1}(\mathbf{Y}_{i} - \mathbf{Y}_{i})^{\top}(\mathbf{Y}_{i})$$

## **MCMC Algorithm**

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$$f(\mathbf{B}|\boldsymbol{\mu}^{\top}, \sigma^{2}, A, \gamma, Y^{\top}) \sim \\ MVN_{d}((\frac{Z_{j}^{\top}Z_{j}}{\sigma^{2}} + A)^{-1}(\frac{Y_{j}^{\top}Z_{j}^{\top} - X_{j}^{\top}Z_{j}\gamma}{\sigma^{2}} + \mu^{\top}A)^{\top}, \frac{Z_{j}^{\top}Z_{j}}{\sigma^{2}} + A)^{-1})$$

- $(NA + \frac{1}{y})^{-1} (\sum_{i=1}^{n} \beta_{i}A)^{\top}, (NA + \frac{1}{y})^{-1})$
- $f(\sigma|B^{\top}, \mu^{\top}, A, \gamma, Y^{\top}) \sim MVN_d((X_i^{\top} \sigma^{-2} I X_i + 400 I)^{-1} (X_i^{\top} \sigma^{-2} I Y_i X_i^{\top} \sigma^{-2} I Z_i \beta_i), (X_i^{\top} \sigma^{-2} I X_i + 400 I)^{-1} )$
- $\bullet f(A|B^{\top}_{-}\sigma^2,\gamma,Y^{\top}) \sim \underline{w}^{-1}(S + \sum_{i}^{n}(\beta_{i} \mu)(\beta_{i} \mu)^{\top}, n + \nu)$
- **5**  $f(\gamma|B^{\top}, \mu^{t}op, \sigma^{2}, A, Y^{\top}) \sim MVN((\frac{X_{j}^{\top}X_{j}}{\sigma^{2}} + 400I)^{-1}(\sum_{i}^{n}Y_{j}^{\top}X_{j} \sum_{i}^{n}X_{j}Z_{j}\beta_{j})^{\top}, (\frac{X_{j}^{\top}X_{j}}{\sigma^{2}} + 400I)^{-1})$

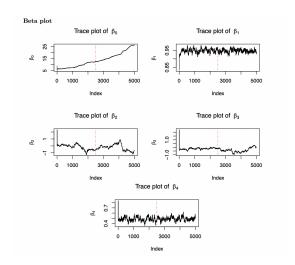
#### **MCMC** Results

#### **Details**

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

## MCMC Results - Beta Plots 1

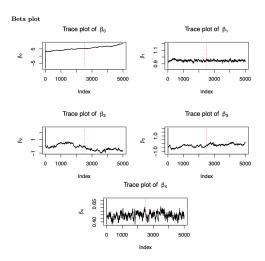
#### MCMC Results - Beta Plots 1



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

#### MCMC Results - Beta Plots 2

#### **MCMC** Results - Beta Plots 2



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