

Hierarchical Bayesian Modeling of Hurricane Trajectories

P8160 Group Project 3 - Markov chain Monte Carlo

Jingchen Chai, Yi Huang, Zining Qi, Ziyi Wang, Ruihan Zhang

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Abstract

A hurricane is a tropical storm with winds that have reached a constant speed of 74 miles per hour or more. Developing a model to predict the wind speed of the hurricane can provide early warning and help communities and individuals prepare for severe weather events. In this study we built a Bayesian model and implemented MCMC algorithm to generate the distribution of corresponding parameters. Most parameters converged well, and the model performed good in predicting the wind speed. Our study also analyzed that there are no significant differences observed between wind speeds in different seasons.

Introduction

Data

ID: ID of hurricanes

Season: In which year the hurricane occurred

Month: In which month the hurricane occurred

Nature: Nature of the hurricane

- ET: Extra Tropical
- DS: Disturbance
- NR: Not Rated
- SS: Sub Tropical
- TS: Tropical Storm

Time: dates and time of the record

Latitude and Longitude: The location of a hurricane check point

Wind.kt: Maximum wind speed (in Knot) at each check point

Background

Exploratory Data Analysis

Data Pre-processing

- We have filtered observations that occurred on a 6-hour intervals. (e.g., hour 0, 6, 12, 18)
- Calculated the lag difference for latitude, longitude and wind speed.
- After data cleaning, we obtained 20293 observations and with 699 different hurricanes.

Methodology

Markov chain Monte Carlo

In our project, we employed a Markov chain Monte Carlo (MCMC) simulation to estimate the parameters of a model that predicts wind speed based on velocity trajectory data. The MCMC algorithm generates samples from the Markov Chain in a way that leads us closer to the desired posterior. In our study, we used two MCMC techniques: the Metropolis-Hastings algorithm and Gibbs sampling.

Hierarchical Bayesian Model

Bayesian hierarchical modeling is a statistical approach that involves writing a model in multiple levels or a hierarchical form to estimate the parameters of the posterior distribution using Bayesian methodology. This

technique assumes that the observed data are generated from a hierarchy of unknown parameters, and it estimates the posterior distribution of these parameters using a Bayesian approach. In other words, Bayesian hierarchical modeling is a way of modeling complex data structures by breaking them down into smaller, more manageable components and using Bayesian analysis to estimate the unknown parameters in each component.

From the Bayes' theorem:

$$\text{posterior distribution} \propto \text{likelihood} \times \text{prior distribution}$$

$$\pi(\theta|X) \propto \pi(X|\theta) \times \pi(\theta)$$

The Hierarchical Bayes

$$\pi(\theta, \alpha|X) \propto \pi(X|\theta) \times \pi(\theta|\alpha) \times \pi(\alpha)$$

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 σ^2 , independent across t .
- $X_i = (x_{i,1}, x_{i,2}, x_{i,3})$ are covariates with fixed effect γ , where $x_{i,1}$ be the month of year when the i -th hurricane started, $x_{i,2}$ be the calendar year of the i hurricane, and $x_{i,3}$ be the type of the i -th hurricane.
- $\beta_i = (\beta_{0,i}, \beta_{1,i}, \dots, \beta_{5,i})$, we assume that $\beta_i \sim N(\mu, \Sigma)$.

Prior Distribution

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

where V is a variance-covariance matrix

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

where d is the dimension of β_i , S is the scale matrix

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

$$P(\sigma) = \frac{2\alpha}{\sigma^2 + \alpha^2} \propto \frac{1}{\sigma^2 + \alpha^2} = \frac{1}{\sigma^2 + 100}$$

Joint Posterior Distribution

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

$$\text{Let } Z_i(t)\beta_i^\top = \beta_{0,i} + \beta_{1,i}Y_i(t) + \beta_{2,i}\Delta_{i,1}(t) + \beta_{3,i}\Delta_{i,2}(t) + \beta_{4,i}\Delta_{i,3}(t) + X_i\gamma + \epsilon_i(t)$$

Where Z_i is the n_i *d covariate matrix for hurricane i.

We can find that

$$Y_i \sim MVN(Z_i\beta_i^T, \sigma^2 I)$$

The likelihood for Y is:

$$\begin{aligned}
f(Y | B, \mu, \sigma, \Sigma, \gamma) &= \prod_{i=1}^n f(Y_i | B, \mu, \Sigma, \sigma) = \\
&\prod_{i=1}^n \frac{1}{\sqrt{2\pi}\sigma} \exp\left\{-\frac{1}{2}(Y_i - Z_i\beta_i - X_i\gamma)^\top (\sigma^2 I)^{-1} (Y_i - Z_i\beta_i - X_i\gamma)\right\} \\
&\propto (\sigma^2)^{-\frac{N}{2}} \prod_{i=1}^n \exp\left\{-\frac{1}{2}(Y_i - Z_i\beta_i - X_i\gamma)^\top (\sigma^2 I)^{-1} (Y_i - Z_i\beta_i - X_i\gamma)\right\}
\end{aligned}$$

For simple notation, let $N = (\sum_i^n n_i)$, representing the total number of unique hurricanes.

The likelihood for \mathbf{B} is:

$$\begin{aligned}
f(B | \mu, \Sigma) &= \prod_{i=1}^n f(B_i | \mu, \Sigma) = \\
&\prod_{i=1}^n \frac{1}{\sqrt{2\pi|\Sigma|}} \exp\left\{-\frac{1}{2}(Y_i - Z_i\beta_i - X_i\gamma)^\top (\sigma^2 I)^{-1} (Y_i - Z_i\beta_i - X_i\gamma)\right\} \\
&\propto (|\Sigma|)^{-\frac{N}{2}} \prod_{i=1}^n \exp\left\{-\frac{1}{2}((\beta_i - \mu)^\top \Sigma^{-1} (\beta_i - \mu))\right\}
\end{aligned}$$

Joint Posterior

By using the Bayesian rule, we can show the posterior distribution for Θ is,

$$\begin{aligned}
\pi(\Theta | Y) &= P(B, \mu, \sigma, \Sigma, \gamma | Y) \propto \underbrace{L(Y | B, \sigma)}_{\text{likelihood of } Y} \underbrace{L(B | \mu, \Sigma)}_{\text{likelihood of } \mathbf{B}} \underbrace{p(\mu)p(\sigma)p(\Sigma)p(\gamma)}_{\text{priors}} \\
&\propto \frac{1}{\sigma^N (\sigma^2 + 10^2)} \prod_{i=1}^n \exp\left\{-\frac{1}{2}(Y_i - Z_i\beta_i - X_i\gamma)^\top (\sigma^2 I)^{-1} (Y_i - Z_i\beta_i - X_i\gamma)\right\} \\
&\times \exp\left\{-\frac{1}{2} \sum_i^n (\beta_i - \mu)^\top \Sigma^{-1} (\beta_i - \mu)\right\} |\Sigma|^{-1} \exp\left\{-\frac{1}{2} \text{tr}(S\Sigma^{-1})\right\} |V|^{-\frac{1}{2}} \\
&\times \exp\left\{-\frac{1}{2} \mu^\top V^{-1} \mu\right\} \\
&\times \exp\{-200\gamma^2\}
\end{aligned}$$

Conditional Posterior Distribution

1. The posterior distribution of B Let $A = \Sigma^{-1}$

$$\begin{aligned}
\pi(\mathbf{B}|Y, \mu^\top, \sigma, \Sigma) &\propto \prod_{i=1}^n \exp\left\{-\frac{1}{2}(Y_i - Z_i\beta_i - X_i\gamma)^\top (\sigma^2 I)^{-1}(Y_i - Z_i\beta_i - X_i\gamma)\right\} \\
&\times \exp\left\{-\frac{1}{2}\sum_i (\beta_i - \mu)^\top \Sigma^{-1}(\beta_i - \mu)\right\} \\
&\propto \prod_{i=1}^n \exp\left\{-\frac{1}{2}(Y_i - Z_i\beta_i - X_i\gamma)^\top (\sigma^2 I)^{-1}(Y_i - Z_i\beta_i - X_i\gamma)\right\} + (\beta_i - \mu)^\top A(\beta_i - \mu)\right\} \\
&\propto \prod_{i=1}^n \exp\left\{-\frac{1}{2}(\beta_i(Z_i^\top (\sigma^2 I)^{-1} Z_i + A)\beta_i^\top - 2(Z_i^\top (\sigma^2 I)^{-1} Y_i - Z_i^\top \gamma X_i (\sigma^2 I)^{-1} + \mu A)\beta_i\right. \\
&\propto \prod_{i=1}^n \exp\left\{-\frac{1}{2}[\beta_i - (Z_i^\top (\sigma^2 I)^{-1} Z_i + A)^{-1}(Z_i^\top (\sigma^2 I)^{-1} Y_i - Z_i^\top \gamma X_i (\sigma^2 I)^{-1} + \mu A)^\top]^\top\right. \\
&\times (Z_i^\top (\sigma^2 I)^{-1} Z_i + A)[\beta_i - (Z_i^\top (\sigma^2 I)^{-1} Z_i + A)^{-1}(Z_i^\top (\sigma^2 I)^{-1} Y_i - Z_i^\top \gamma X_i (\sigma^2 I)^{-1} + \mu A)^\top]\right\}
\end{aligned}$$

$$\beta_i \sim MVN(N^{-1}M, N^{-1}), \text{ where } N = \frac{Z_i^\top Z_i}{\sigma^2} + A, M = \frac{Z_i^\top Y_i - Z_i^\top X_i \gamma}{\sigma^2} + \mu A$$

2. The posterior distribution of μ

$$\begin{aligned}
\pi(\mu|B, \sigma, A, \gamma) &\propto \exp\left\{-\frac{\mu^\top V^{-1}\mu}{2}\right\} \prod_{i=1}^N \exp\left\{-\frac{(\beta_i - \mu)^\top A(\beta_i - \mu)}{2}\right\} \\
&= \exp\left\{\sum_i \left[-\frac{1}{2}(\mu^\top (A - \frac{1}{N}V^{-1})\mu - 2\mu^\top A\beta_i + \beta_i^\top A\beta_i)\right]\right\} \\
&= \exp\left\{-\frac{1}{2}(\mu^\top (NA - V^{-1})\mu - 2\mu^\top \sum_i (A\beta_i) + \beta_i^\top A\beta_i)\right\}
\end{aligned}$$

$$\mu \sim MVN(M^{-1}N, M^{-1}), \text{ where } M = NA - V^{-1} \text{ and } N = \sum_i (A\beta_i)$$

3. The posterior distribution of Σ

$$\begin{aligned}
\pi(\Sigma|B, \mu, \gamma, \sigma, Y) &\propto |\Sigma|^{-\frac{(N+v+d+1)}{2}} \exp\left\{-\frac{1}{2}\left(\sum_i (\beta_i - \mu)^\top A(\beta_i - \mu) + \text{tr}(SA)\right)\right\} \\
&\propto |\Sigma|^{-\frac{(N+v+d+1)}{2}} \exp\left\{-\frac{1}{2}\text{tr}\left(S + \sum_i (\beta_i - \mu)(\beta_i - \mu)^\top\right)A\right\} \\
\Sigma &\sim w^{-1}\left(S + \sum_i (\beta_i - \mu)(\beta_i - \mu)^\top, N + v\right)
\end{aligned}$$

4. The posterior distribution of γ

$$\begin{aligned}
\pi(\gamma|B, \mu, \Sigma, \sigma, Y) &\propto \prod_{i=1}^N \exp\left\{-\frac{1}{2}(Y_i - Z_i\beta_i - X_i\gamma)^\top (\sigma^2 I)^{-1}(Y_i - Z_i\beta_i - X_i\gamma)\right\} \times \exp\left\{-\frac{400\gamma^\top \gamma}{2}\right\} \\
&\propto \exp\left\{-\frac{1}{2}\sum_i \gamma^\top (X_i^\top \sigma^{-2} I X_i + 400N^{-1}I)\gamma - 2\gamma^\top (X_i^\top \sigma^{-2} I Y_i - X_i^\top \sigma^{-2} I Z_i \beta_i)\right. \\
&\quad \left.+ Y_i^\top \sigma^{-2} I Y_i - 2Y_i^\top \sigma^{-2} I Z_i \beta_i + \beta_i^\top Z_i^\top \sigma^{-2} I Z_i \beta_i\right\}
\end{aligned}$$

$\gamma \sim MVN(M^{-1}N, M^{-1})$, where $M = \frac{\sum_i^N X_i^\top X_i}{\sigma^2} + 400I$ and $N = \frac{\sum_i^N (X_i^\top Y_i - X_i^\top Z_i \beta_i)}{\sigma^2}$

5. The posterior distribution of σ

$$\begin{aligned} \pi(\sigma|Y, B, \mu, \Sigma, \gamma) &\propto \frac{1}{\sigma^N(\sigma^2 + 10^2)} \\ &\times \prod_{i=1}^n \exp \left\{ -\frac{1}{2(\sigma^2 I)} (Y_i - Z_i \beta_i - X_i \gamma)^\top (Y_i - Z_i \beta_i - X_i \gamma) \right\} \end{aligned}$$

σ does not have a close distribution.

MCMC Algorithm

After deriving the conditional posterior of parameter that we want to estimate, the next step is to apply these conditional posterior to the MCMC Algorithm. Our MCMC algorithm is a hybrid of Metropolis-Hastings and Gibb Sampling.

Metropolis-Hastings

From the conditional posterior of σ , it is hard to find a closed form distribution for it, unlike other parameters. Here, we apply Metropolis-Hastings to generate new σ . The detailed steps of Metropolis-Hasting is shown below:

Algorithm 1 MCMC: Metropolis-Hastings

Require: Target distribution $\pi(\sigma)$

for $i = 1$ to 1000 **do**

1. Proposed $\sigma_{proposed} = \sigma^{(i-1)} + (U - 0.5) * 2 * a$, where $U \sim \text{Uniform}(0,1)$, a is step size

2. Calculate acceptance rate $\alpha_{XY} = \min(0, \frac{\pi(\sigma_{proposed})}{\pi(\sigma^{(i-1)})})$

3. If $U < \alpha_{XY}$: $\sigma^{(i)} = \sigma_{proposed}$, else $\sigma^{(i)} = \sigma^{(i-1)}$

end for

$\sigma_k = \sum_{i=801}^{1000} \frac{\sigma^{(i)}}{200}$, where k is the iteration of Gibb Sampling

The target distribution is the conditional posterior of σ . By setting the step size to 0.5, the acceptance rate reaches 43.5%, which is acceptable. The new sigma generated for Gibb Sampling will be the mean of next 200 values in the chain.

Gibb Sampling

After defining the Metropolis-Hastings algorithm to generate σ , we combine the Metropolis-Hastings with Gibb Sampling. We first initialized the parameters to start the algorithm. The parameters in Gibb Sampling will be updated component-wise. For each parameter to be updated, it always conditioned on the most recent values of other parameters. More precisely,

Algorithm 2 MCMC: Gibb Sampling

Require: Initialize $B, \mu, \sigma, \Sigma, \gamma$

for $k = 1$ to 5000 **do**

1. Generate β_i^k for i^{th} hurricane from $\pi(B|Y, \mu^{k-1}, \sigma^{k-1}, \Sigma^{k-1}, \gamma^{k-1})$

2. Generate μ^k from $\pi(\mu|Y, B^k, \sigma^{k-1}, \Sigma^{k-1}, \gamma^{k-1})$

3. Generate σ_k from the Metropolis-Hastings steps

4. Generate Σ_k from $\pi(\Sigma|Y, B_k, \mu_k, \sigma_k, \gamma_{k-1})$

5. Generate γ_k from $\pi(\gamma|Y, B_k, \mu_k, \sigma_k, \Sigma_k)$

end for

We have tested different start values for MCMC algorithm, the result chain behave similarly. We finally decide to initialize the parameters by using the results from fitting generalized linear mixed model in R. \mathbf{B} is a $5 * 699$ matrix, $\boldsymbol{\mu}$ is a $5 * 1$ matrix, σ is a number, $\boldsymbol{\Sigma}$ is a $5 * 5$ matrix, and $\boldsymbol{\gamma}$ is a $14 * 1$ matrix.

Results

In Markov Chain Monte Carlo, determining the appropriate number of iterations can depend on many factors such as the complexity of the model, the size of the dataset, etc. Therefore, it is difficult to make a general statement about a specific number of iterations that will be sufficient for all MCMC simulations. In our algorithm, we believe for most of the parameters, 5000 iterations reached the stationary of their posterior distribution. For convergence diagnostics, we generate trace plots, autocorrelation plots, and histograms.

Random effect parameter

Figure 1 shows convergence plots of \mathbf{B} . β_1 takes only a few steps to reach stationary. The trace plot shows the history of our parameter β_1 across iterations of the chain. This chain appears most likely to converge with an average value of about 0.95. Similarly for β_4 , the chain appears most likely to converge with an average value of about 0.48. β_2 and β_3 need to take more iterations to achieve convergence. In Figure 2, we extract Hurricane George 1951 from the data to check its β convergence plots and distribution. We can see on trace plot of 5000 iterations for the selected parameter, each of the distributions are relatively normal with some heavy tails in β_0 .

The Convergence plot of σ^2 suggests that the chain is mixing well and that the algorithm is converging to its posterior distribution of σ^2 . After iteration 500, this chain appears to converge with an average value of 34.5 This also indicates that the estimated values of σ^2 are becoming more independent and less influenced by their past values as iterations increase.

Figure 1

Figure 2 shows the selected \mathbf{B} : Hurricane GEORGE.1951

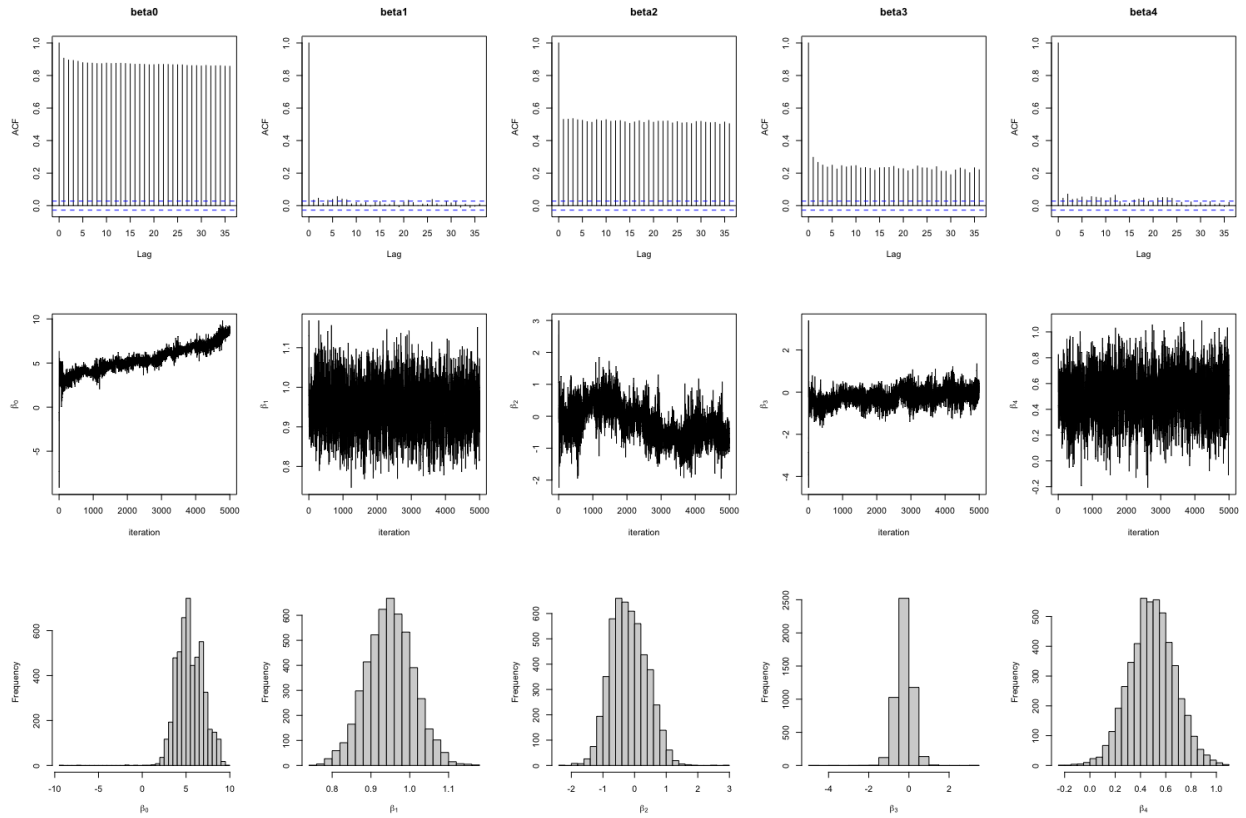


Figure 2

Fix effect parameter γ

Limitation and Discussion

Conclusion

References

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Contributions

A First section of Appendix

B Section section of Appendix