P8160 - Bayesian Modeling of Hurricane Trajectories

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Introduction

Data Praparation

- Self-join was performed to generate data for Gibbs sampling
- For each hurricane, 80%/20% of records were randomly assigned to the training/test dataset. Hurricanes with less than 5 records were removed.

Gibbs Sampling

Initialize $\Theta_0 = (\mathbf{B}_0, \boldsymbol{\mu}_0, \sigma_0^2, \Sigma_0)$

for iteration i = 1,2,... **do**

Sample $\mathbf{B}_i \sim \pi(\mathbf{B}|\boldsymbol{\mu}_{i-1}, \sigma_{i-1}^2, \Sigma_{i-1}, \mathbf{Y})$

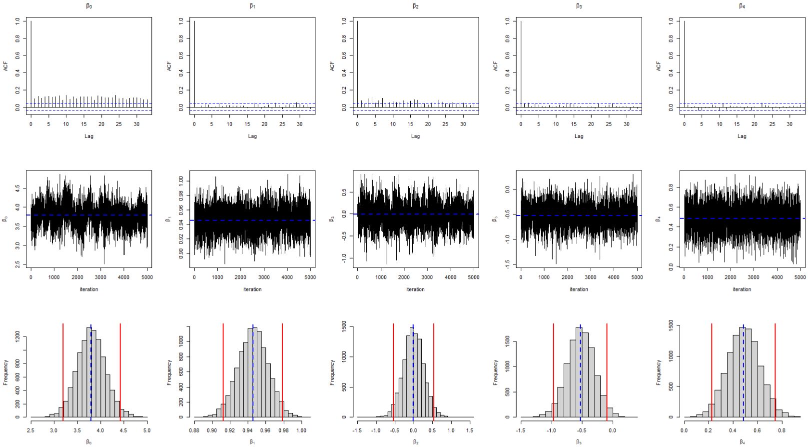
Sample $\boldsymbol{\mu}_i \sim \pi(\boldsymbol{\mu}|\mathbf{B}_i, \sigma_{i-1}^2, \Sigma_{i-1}, \mathbf{Y})$

Sample $\sigma_i^2 \sim \pi(\sigma^2|\mathbf{B}_i, \boldsymbol{\mu}_i, \Sigma_{i-1}, \mathbf{Y})$

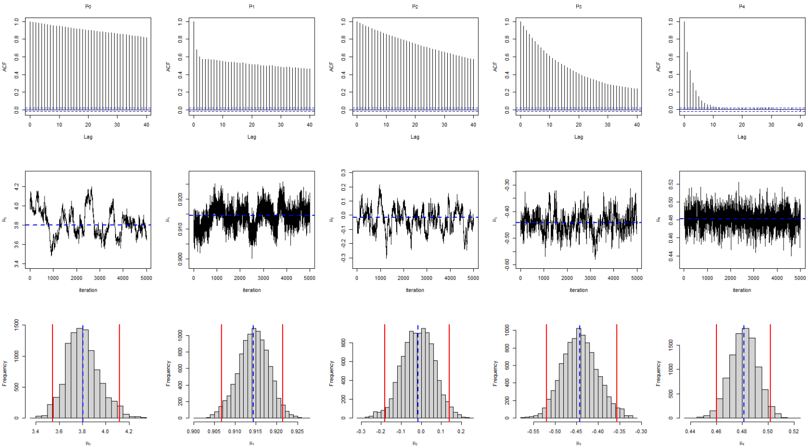
Sample $\Sigma_i \sim \pi(\Sigma|\mathbf{B}_i, \boldsymbol{\mu}_i, \sigma_i^2, \mathbf{Y})$

end for

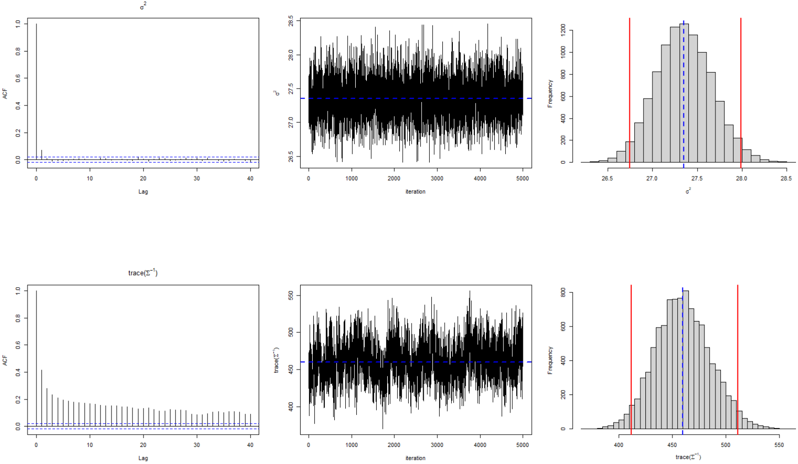
Results



Results

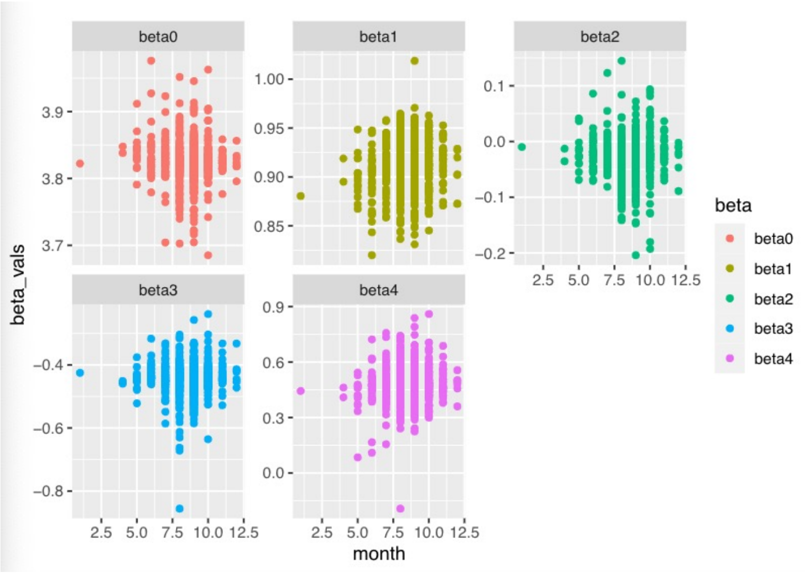


Results



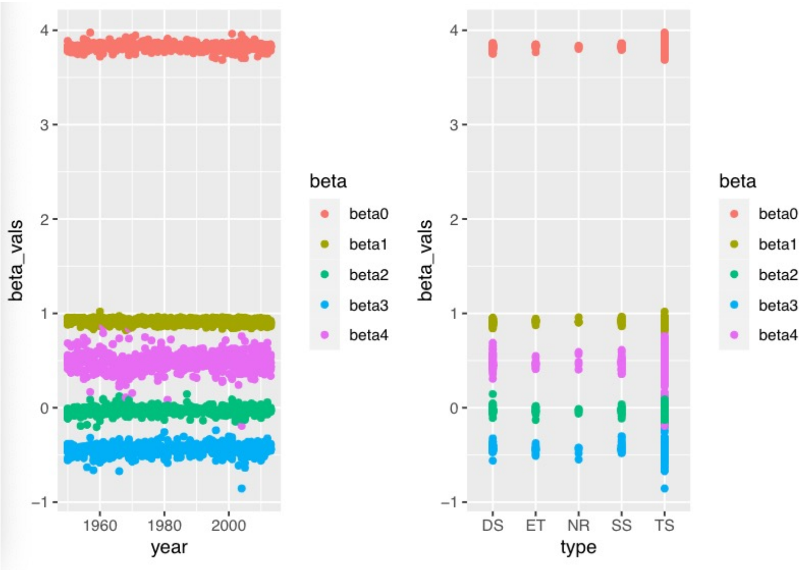
σ²
ACF
Lag
iteration
σ²
Frequency
σ²
trace(Σ⁻¹)
ACF
Lag
trace(Σ⁻¹)
iteration
Frequency
trace(Σ⁻¹)

EDA of β_i



beta0
beta1
beta2
beta3
beta4
beta_vals
month
3.9
3.8
3.7
1.00
0.95
0.90
0.85
0.1
0.0
−0.1
−0.2
−0.4
−0.6
−0.8
0.9
0.6
0.3
0.0
2.5
5.0
7.5
10.0
12.5
beta
beta0
beta1
beta2
beta3
beta4

EDA of β_i



beta_vals
year
1960
1980
2000
4
3
2
1
0
−1
beta
beta0
beta1
beta2
beta3
beta4
type
DS
ET
NR
SS
TS

Seasonal Analysis

Model 1:
$$Beta_i = \alpha_0 + \alpha_1 I(\mathrm{Month} = M) + \alpha_2 \times \mathrm{Year} + \alpha_3 I(\mathrm{Type} = N)$$

Coefficients of Model 1 for β_i

	Beta0		Beta1		Beta2		Beta3		Beta4	
	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)
(Intercept)	3.8722305	0.0000000	1.4200232	0.0000000	-0.0807485	0.6123701	-0.7395516	0.0012896	0.8052773	0.0590557
factor(month)4	0.0211436	0.5897652	0.0316515	0.3472330	-0.0115682	0.7896176	-0.0234552	0.7064830	-0.0053003	0.9635270
factor(month)5	0.0202412	0.5405684	0.0281544	0.3215509	-0.0113447	0.7563959	-0.0120033	0.8192595	-0.0390352	0.6897011
factor(month)6	0.0159306	0.6239449	0.0246013	0.3779221	-0.0148705	0.6789563	0.0098662	0.8483886	0.0112067	0.9071129
factor(month)7	0.0078141	0.8090619	0.0404591	0.1453332	-0.0165819	0.6428643	-0.0027461	0.9573635	0.0199011	0.8350861
factor(month)8	0.0019068	0.9527290	0.0425000	0.1241205	-0.0260312	0.4643250	-0.0112584	0.8255944	0.0229217	0.8095080
factor(month)9	0.0009337	0.9768273	0.0472980	0.0868820	-0.0233893	0.5105760	-0.0075900	0.8818256	0.0389302	0.6820459
factor(month)10	0.0074737	0.8163761	0.0411045	0.1371659	-0.0168883	0.6351370	-0.0007253	0.9886799	0.0268667	0.7776519
factor(month)11	0.0057884	0.8588527	0.0448708	0.1086605	-0.0079430	0.8253327	0.0043686	0.9326594	0.0387334	0.6872898
factor(month)12	0.0048248	0.8874129	0.0308019	0.2926123	-0.0208686	0.5797518	0.0072339	0.8936869	0.0283150	0.7786590
year	-0.0000290	0.6794636	-0.0002769	0.0000050	0.0000378	0.6260392	0.0001587	0.1544308	-0.0001713	0.4088111
factor(type)ET	0.0075408	0.4379949	0.0086401	0.3006911	-0.0108462	0.3131136	-0.0192894	0.2118151	-0.0222770	0.4382889
factor(type)NR	0.0005575	0.9705947	0.0072156	0.5784605	-0.0132239	0.4292334	-0.0418405	0.0819304	0.0070952	0.8739144
factor(type)SS	0.0074733	0.2505823	0.0082071	0.1417607	-0.0038667	0.5906999	0.0003254	0.9748646	-0.0225589	0.2407159
factor(type)TS	0.0057948	0.2474418	0.0009877	0.8182988	-0.0024415	0.6592917	-0.0141969	0.0746373	-0.0108813	0.4623952

Seasonal Analysis

Model 2:

$$Beta_i = \alpha_0 + \alpha_1 I(\text{Season} = S) + \alpha_2 \times \text{Year} + \alpha_3 I(\text{Type} = N)$$

Coefficients of Model 2 for β_i

	Beta 0		Beta 1		Beta 2		Beta 3		Beta 4	
	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)
(Intercept)	3.8777185	0.0000000	1.4515958	0.0000000	-0.1108749	0.4777627	-0.7432739	0.0009368	0.8246599	0.0469629
factor(season)spring	0.0165743	0.0386414	-0.0161701	0.0195181	0.0080903	0.3613959	-0.0095303	0.4529259	-0.0700505	0.0029939
factor(season)summer	0.0017442	0.4921921	-0.0054774	0.0126824	-0.0021923	0.4356701	-0.0020772	0.6061277	-0.0145208	0.0520294
factor(season)winter	0.0004419	0.9695014	-0.0175939	0.0782636	0.0012626	0.9214169	0.0101974	0.5781775	-0.0099913	0.7687012
year	-0.0000297	0.6721280	-0.0002706	0.0000093	0.0000429	0.5814228	0.0001589	0.1539417	-0.0001639	0.4270083
factor(type)ET	0.0090086	0.3383681	0.0086688	0.2860439	-0.0058182	0.5765098	-0.0167604	0.2616162	-0.0206719	0.4547698
factor(type)NR	0.0017339	0.9077767	0.0079185	0.5401551	-0.0073224	0.6586863	-0.0384250	0.1059825	0.0085343	0.8462012
factor(type)SS	0.0077248	0.2318002	0.0080589	0.1486481	-0.0023967	0.7374924	0.0006525	0.9492157	-0.0222179	0.2419930
factor(type)TS	0.0047623	0.3404235	0.0024950	0.5629051	-0.0029696	0.5913088	-0.0157040	0.0477883	-0.0093683	0.5233984

Forcasting Hurricane Impact

ID: ID of the hurricanes
Season: In which year the hurricane occurred
Month: In which month the hurricane occurred
Nature: Nature of the hurricane
Damage: Financial loss (in Billion U.S. dollars) caused by hurricanes
Deaths: Number of death caused by hurricanes
Maxspeed: Maximum recorded wind speed of the hurricane
Meanspeed: Average wind speed of the hurricane
Maxpressure: Maximum recorded central pressure of the hurricane
Meanpressure: Average central pressure of the hurricane
Hours: Duration of the hurricane in hours
Total.Pop: Total affected population
Percent.Poor: % affected population that reside in low GDP counties
Percent.USA: % affected population that reside in the United States

LASSO Model for Damage

	Coefficients
(Intercept)	-533.5099174
season	3.3837824
deaths	0.0000000
monthJuly	0.0000000
monthJune	0.0000000
monthNovember	0.0000000
monthOctober	0.0000000
monthSeptember	0.0000000
natureNR	0.0000000
natureTS	0.0000000
maxspeed	1.2117851
meanspeed	0.0000000
maxpressure	0.0000000
meanpressure	0.0000000
hours	0.0000000
total_pop	0.3187361
percent_poor	0.0000000
percent_usa	0.7073409
beta0	0.0000000
beta1	0.0000000
beta2	0.0000000
beta3	0.0000000
beta4	0.0000000

Refitted Linear Regression Model

Model: $Y = \gamma_0 + \gamma_1$ x season $+ \gamma_2$ x maxspeed $+ \gamma_3$ x total_pop $+ \gamma_4$ x percent_usa

	Coefficients
(Intercept)	-1316.7386136
season	0.6485139
maxspeed	0.1968674
total_pop	0.0000033
percent_usa	0.1356486

Poisson Model for Dealths

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-199.5331639	11.8792784	-16.7967411	0.0000000
season	-0.0404185	0.0028048	-14.4104991	0.0000000
damage	0.0220163	0.0005679	38.7649762	0.0000000
monthJuly	-10.2286750	0.1604645	-63.7441688	0.0000000
monthJune	0.3928062	0.0989170	3.9710698	0.0000716
monthNovember	1.8733767	0.1664682	11.2536625	0.0000000
monthOctober	-1.6041896	0.0787720	-20.3649754	0.0000000
monthSeptember	1.2490015	0.0575033	21.7205350	0.0000000
natureNR	2.0903864	0.1371766	15.2386495	0.0000000
natureTS	-1.1903051	0.1118619	-10.6408484	0.0000000
maxspeed	0.0035207	0.0013988	2.5168778	0.0118400
meanspeed	-0.1978651	0.0039977	-49.4953412	0.0000000
maxpressure	0.0048106	0.0075485	0.6372945	0.5239331
meanpressure	0.0021204	0.0001759	12.0515409	0.0000000
total_pop	0.0000009	0.0000000	31.4237737	0.0000000
percent_poor	0.0873434	0.0010058	86.8433730	0.0000000
percent_usa	-0.0080185	0.0004884	-16.4173000	0.0000000
beta0	41.3531048	0.5634443	73.3934206	0.0000000
beta1	132.8784572	1.9305164	68.8305252	0.0000000
beta2	-10.7339527	0.5001340	-21.4621524	0.0000000
beta3	-0.4736994	0.5091748	-0.9303277	0.3522014
beta4	4.4919244	0.1971025	22.7897893	0.0000000

Discussion

Strength & Limitation of MCMC methods

- Bypass coefficient optimization process and directly sample coefficients from their assumed distributions
- Often computationally expensive and can be inefficient
- Convergence is not guaranteed

Why Non-convergence?

- $\beta_i \sim N(\beta, \Sigma)$ may be a too strong assumption

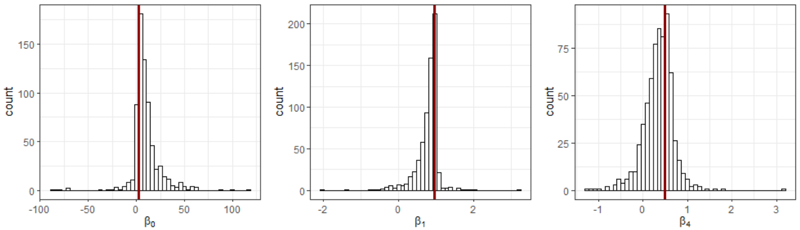


Figure 1: Distribution of β_is obtained by performing OLS for each hurricane (red line: β obtained by performing OLS on the whole training dataset)

- **Future work**: use a more adequate distribution assumption of β_i which can account for skewness