

# **P8160 - Project 3**

## **Baysian modeling of hurricane**

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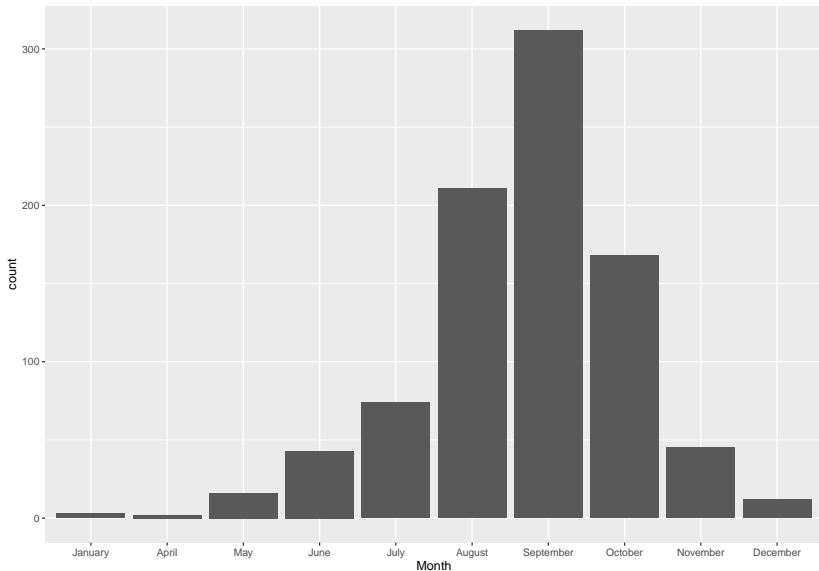
# Introduction

- ▶ Hurricanes can result in death and economical damage
- ▶ There is an increasing desire to predict the speed and damage of the hurricanes
- ▶ Use Bayesian Model and Markov Chain Monte Carlo algorithm
  - ▶ Predict the wind speed of hurricanes
  - ▶ Study how hurricanes is related to death and financial loss

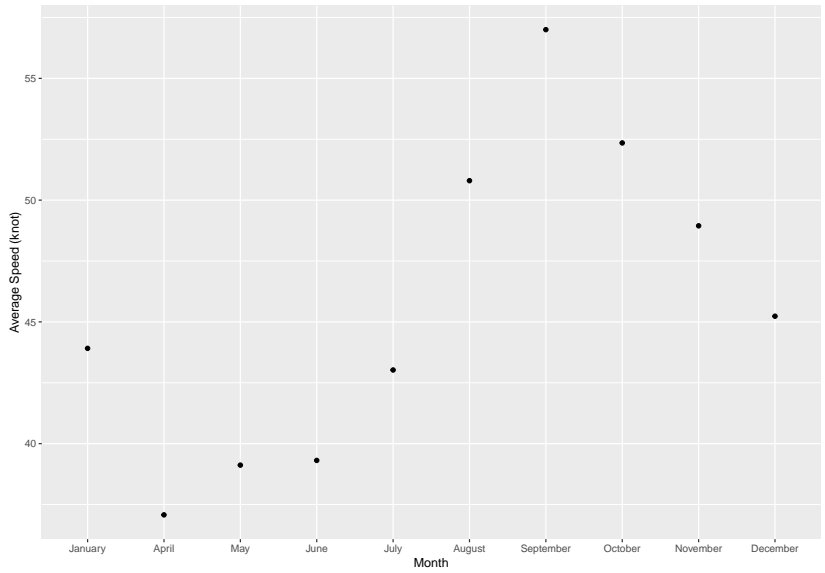
# Dataset

- ▶ Hurrican703 dataset: 22038 observations  $\times$  8 variables
  - ▶ 702 hurricanes in the North Atlantic area in year 1950-2013 with tra
- ▶ Processed dataset: add 5 more variables into hurrican703
- ▶ Hurricanoutcome2 dataset: 43 observations  $\times$  14 variables

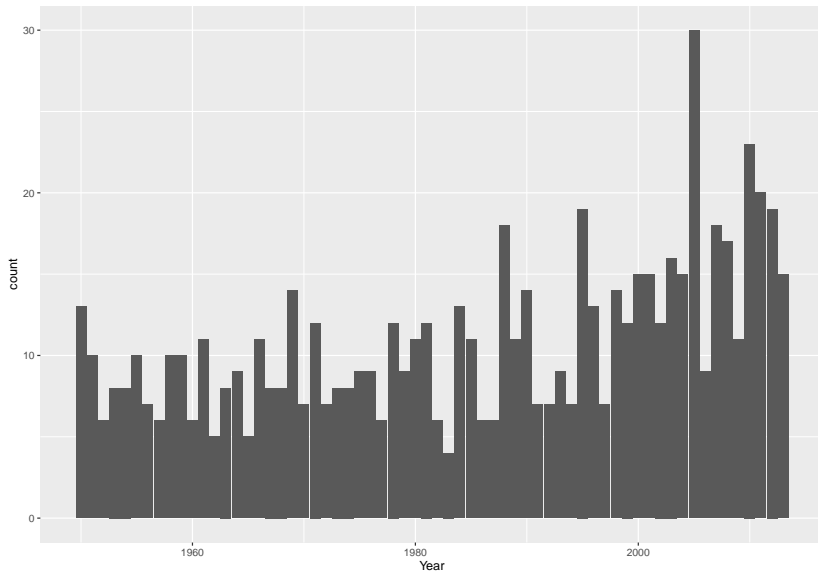
# EDA - Count of Hurricanes in Each Month



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

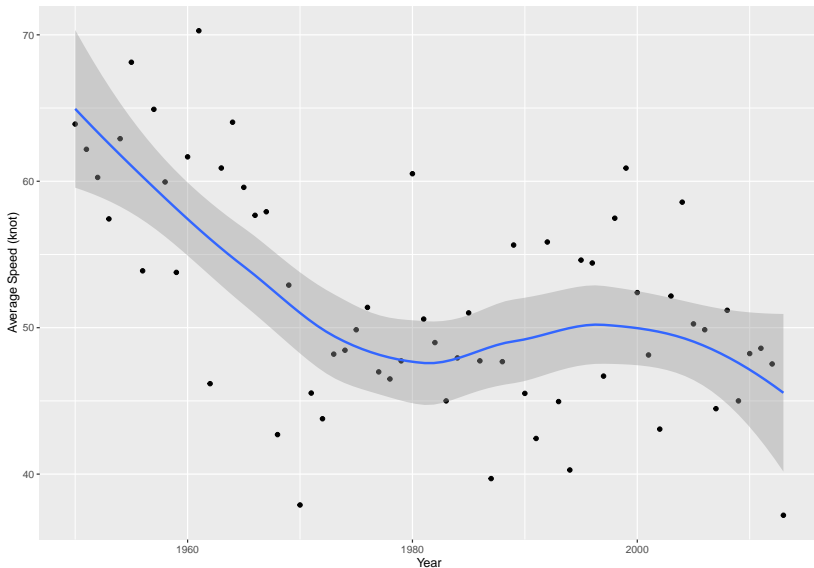


# EDA - Count of Hurricanes in Each Year

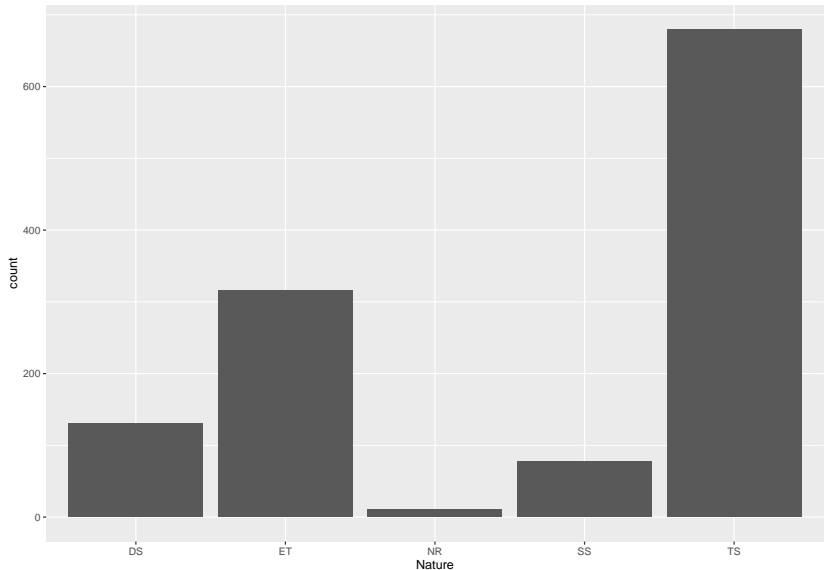


# EDA - Average Speed (knot) of Hurricanes in Each Year

```
## `geom_smooth()` using formula 'y ~ x'
```

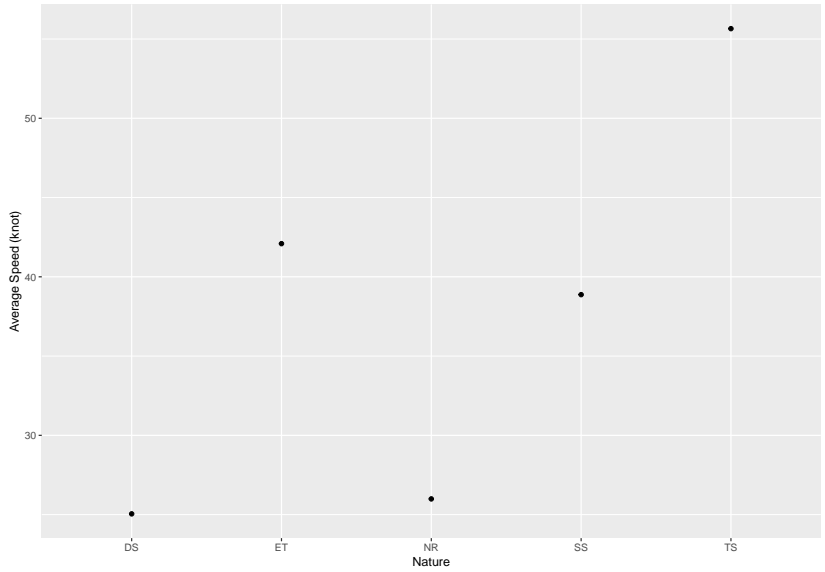


# EDA - Count of Hurricanes in Each Nature





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



## Joint posterior

$$\begin{aligned}\pi(\Theta|Y) &= \pi(\mathbf{B}^\top, \mu^\top, \sigma^2, \Sigma \mid Y) \\ &\propto \prod_{i=1}^n f(Y_i \mid \beta_i, \sigma^2) \prod_{i=1}^n \pi(\beta_i \mid \mu, \Sigma) P(\sigma^2) P(\mu) P(\Sigma^{-1}) \\ &\propto \prod_{i=1}^n \left\{ (2\pi\sigma^2)^{-m_i/2} \exp \left\{ -\frac{1}{2} (Y_i - X_i \beta_i^\top)^\top (\sigma^2 I)^{-1} (Y_i - X_i \beta_i^\top) \right\} \right. \\ &\quad \times \left. \prod_{i=1}^n \left\{ \det(2\pi\Sigma)^{-\frac{1}{2}} \exp \left\{ -\frac{1}{2} (\beta_i - \mu) \Sigma^{-1} (\beta_i - \mu)^\top \right\} \right\} \times \frac{1}{\sigma^2} \right\} \times \dots\end{aligned}$$

# MCMC algorithm

# Conditional Posterior

- ▶ To apply MCMC using Gibbs sampling, we need to find conditional posterior distribution of each parameter, then we can implement Gibbs sampling on these conditional posterior distributions.

- ▶  $\pi(\mathbf{B}|Y, \mu^\top, \sigma^2, \Sigma)$

- ▶  $\pi(\sigma^2|Y, \mathbf{B}^\top, \mu^\top, \Sigma)$



# Seasonal Difference Exploration

	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)	4.5142875	0.0000000	1.3448481	0.0000000	-0.1056332	0.8629385	-1.0267628	0.001781	0.3051312	0.3817170
season	-0.0003543	0.0497902	-0.0002178	0.0001332	0.0000878	0.7757368	0.0003188	0.053474	0.0000902	0.6072986

Fitted results of beta models

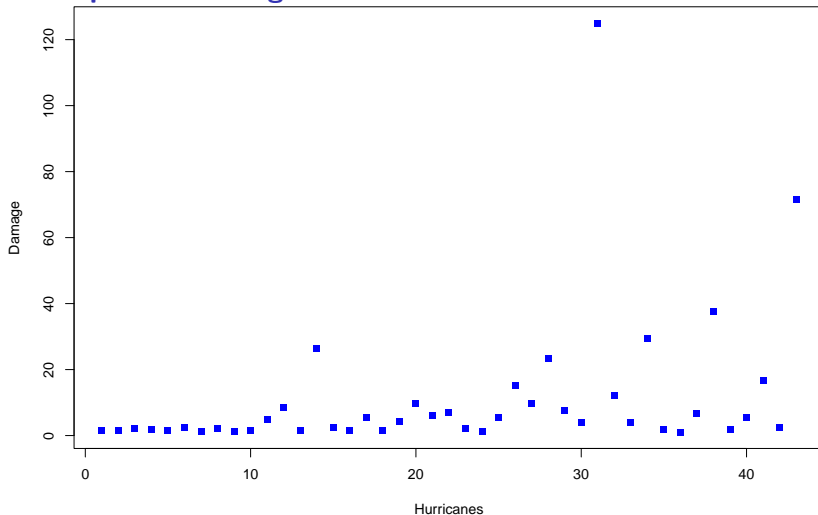
# Seasonal Difference Exploration

	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)	4.4810021	0.0000000	1.3431063	0.0000000	0.0413063	0.9506172	-0.8336700	0.0185275	0.2890273	0.4482640
monthApril	0.0232609	0.8346449	0.0147943	0.6696787	0.0165579	0.9306863	0.0416468	0.6796126	0.0361823	0.7393892
monthMay	0.0259813	0.7827813	-0.0001180	0.9967888	0.0708822	0.6597505	0.0632772	0.4581672	-0.0162907	0.8594231
monthJune	0.0275693	0.7650618	0.0053935	0.8509869	-0.0070875	0.9641298	0.0556884	0.5047909	0.0237694	0.7918014
monthJuly	0.0125400	0.8914489	0.0154032	0.5901741	-0.0090910	0.9538180	0.0361214	0.6640154	0.0130817	0.8840332
monthAugust	-0.0198034	0.8284715	0.0233206	0.4124181	-0.0522548	0.7378961	0.0123691	0.8811234	0.0312427	0.7261962
monthSeptember	-0.0070528	0.9384385	0.0261005	0.3585599	-0.0361073	0.8169707	0.0212965	0.7966351	0.0444835	0.6177631
monthOctober	0.0093435	0.9185853	0.0210829	0.4587183	-0.0286163	0.8546050	0.0341549	0.6796975	0.0350505	0.6944480
monthNovember	0.0145692	0.8748155	0.0246144	0.3925264	0.0239972	0.8792681	0.0263450	0.7529105	0.0209069	0.8168323
monthDecember	0.0057977	0.9526542	0.0088244	0.7715305	-0.0543131	0.7447475	0.0422468	0.6326060	0.0114196	0.9046290
season	-0.0003419	0.0717253	-0.0002252	0.0001471	0.0000365	0.9101708	0.0002184	0.2032812	0.0000905	0.6249586
natureET	0.0008449	0.9774141	0.0037334	0.6877086	-0.0702038	0.1687975	-0.0263888	0.3286540	-0.0209217	0.4726774
natureNR	0.0008122	0.9866387	-0.0146142	0.3331114	0.0058967	0.9432660	0.0030556	0.9444979	-0.0217275	0.6462854
natureSS	0.0141564	0.4904257	-0.0032999	0.6021721	-0.0013517	0.9692484	0.0126339	0.4964264	-0.0238538	0.2339965
natureTS	0.0118370	0.4785102	-0.0059979	0.2486925	-0.0154533	0.5880814	-0.0231521	0.1258337	-0.0174987	0.2832214

Fitted results of beta models for only the year variable

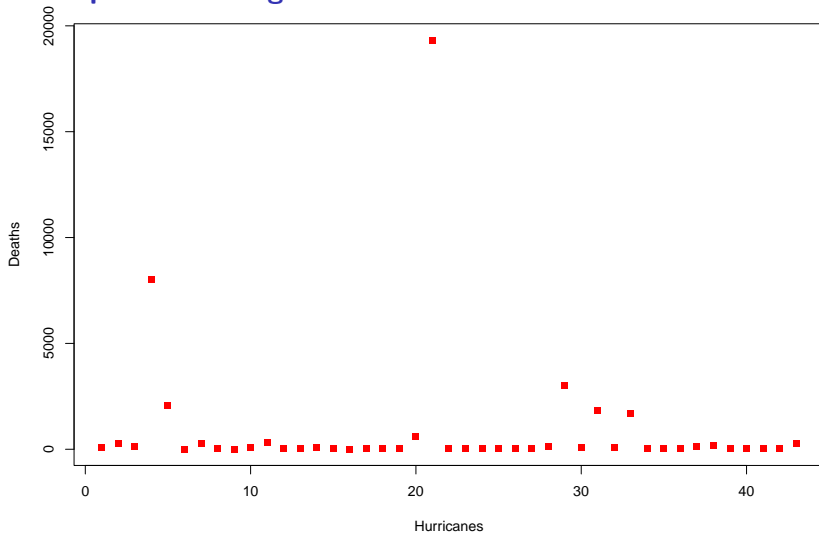
# Predictions of Damage and Deaths

Basic plot of Damage and Deaths



# Predictions of Damage and Deaths

Basic plot of Damage and Deaths





# Coefficient Table

[1]	" id	intercept	beta1	beta2	beta3	beta4 "
[2]	" :-----	-----:	-----:	-----:	-----:	-----: "
[3]	" agnes.1972	3.950974	0.9224097	0.0059532	-0.3103372	0.5453543 "
[4]	" alex.2010	3.798737	0.9370333	0.0698849	-0.3937358	0.5400187 "
[5]	" alicia.1983	3.897408	0.9036878	-0.0748341	-0.3994486	0.5477718 "
[6]	" allen.1980	3.687070	0.9655304	0.1306393	-0.5460144	0.5466129 "
[7]	" andrew.1992	3.676279	0.9375384	-0.2843257	-0.5782973	0.5370158 "
[8]	" betsy.1965	3.808396	0.9513766	-0.4500720	-0.3890718	0.4244575 "
[9]	" bob.1991	3.629466	0.9232143	0.0279527	-0.5751636	0.4382048 "
[10]	" camille.1969	3.994355	0.9355674	0.0729188	-0.5734830	0.6703910 "

Fitted results of beta models

# Predict Damage

	term	estimate	std.error	statistic	p.value
1	(Intercept)	-2.179428e+02	63.786161983	-3.416772	6.336828e-04
2	intercept	5.044916e+00	0.872632934	5.781258	7.414400e-09
3	beta1	6.283543e+01	14.027126920	4.479565	7.479523e-06
4	beta2	-1.095810e+00	0.424325439	-2.582476	9.809426e-03
5	beta3	3.378223e+00	0.816050104	4.139725	3.477231e-05
6	nobs	4.921117e-02	0.008036275	6.123630	9.146733e-10
7	Season	7.497698e-02	0.012627373	5.937655	2.891284e-09
8	MonthJune	-3.416174e+00	0.762110791	-4.482516	7.376795e-06
9	MonthNovember	-1.902107e+00	0.789148853	-2.410327	1.593822e-02
10	MonthOctober	-1.290673e+00	0.298201079	-4.328198	1.503344e-05
11	MonthSeptember	-1.764116e+00	0.243173467	-7.254558	4.029764e-13
12	NatureNR	-4.317468e+00	1.126675716	-3.832042	1.270843e-04
13	NatureTS	-2.038481e+00	0.452900892	-4.500942	6.765302e-06
14	Maxspeed	5.044572e-02	0.006764325	7.457613	8.810369e-14
15	Meanspeed	-6.565465e-02	0.015403789	-4.262240	2.023877e-05
16	Percent.Poor	-3.819578e-02	0.005858677	-6.519522	7.053169e-11
17	Percent.USA	-4.630755e-03	0.002315352	-2.000023	4.549783e-02

Coefficients of damage prediction model

# Predict Deaths

	term	estimate	std.error	statistic	p.value
1	(Intercept)	1.164978e+02	1.257956e+01	9.260883	2.027487e-20
2	Intercept	1.167475e+01	2.564192e-01	45.529931	0.000000e+00
3	beta1	1.141195e+02	2.200144e+00	51.869091	0.000000e+00
4	beta2	5.528798e+00	1.226329e-01	45.084128	0.000000e+00
5	beta3	8.561691e+00	2.853214e-01	30.007184	7.908823e-198
6	beta4	-1.049211e+01	3.058279e-01	-34.307225	6.123346e-258
7	nobs	3.430943e-03	1.116605e-03	3.072657	2.121619e-03
8	Season	6.102077e-03	2.093747e-03	2.914429	3.563401e-03
9	MonthJuly	-1.183782e+00	1.448847e-01	-8.170505	3.071002e-16
10	MonthJune	-1.291597e+00	8.968191e-02	-14.401980	5.028215e-47
11	MonthNovember	-2.533192e+00	1.551869e-01	-16.323490	6.718278e-60
12	MonthOctober	-1.546676e+00	6.466487e-02	-23.918335	1.974205e-126
13	MonthSeptember	-2.751167e-01	4.588850e-02	-5.995331	2.030720e-09
14	NatureNR	2.348783e+00	1.290216e-01	18.204563	4.748263e-74
15	NatureTS	3.563406e+00	1.209962e-01	29.450564	1.238185e-190
16	Meanspeed	-3.676417e-02	3.143216e-03	-11.696356	1.330451e-31
17	Maxpressure	-2.686076e-01	9.670821e-03	-27.775052	8.684053e-170
18	Meanpressure	5.377225e-03	2.009523e-04	26.758717	9.775966e-158
19	Total.Pop	9.410461e-07	2.587520e-08	36.368659	1.332659e-289
20	Percent.Poor	3.599824e-02	8.024514e-04	44.860342	0.000000e+00
21	Percent.USA	-7.214139e-03	5.570867e-04	-12.949761	2.356879e-38

Coefficients of deaths prediction model