P8160 - Project 3 Baysian modeling of hurricane

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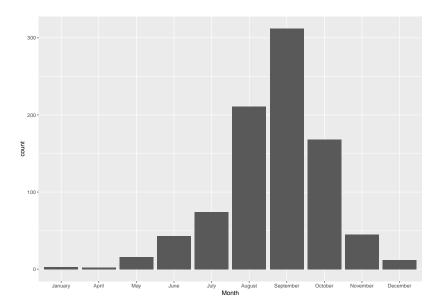
Introduction

- 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

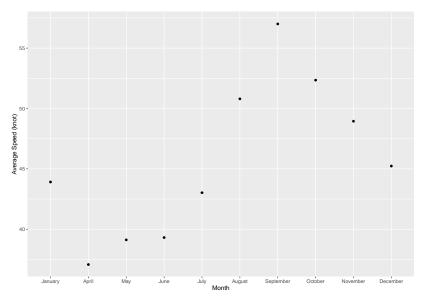
Dataset

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

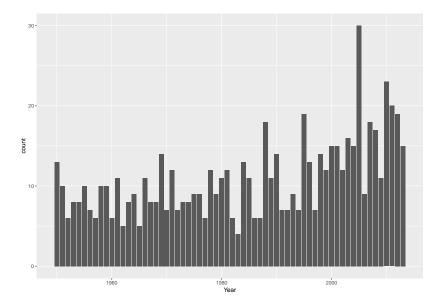
EDA - Count of Hurricanes in Each Month



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

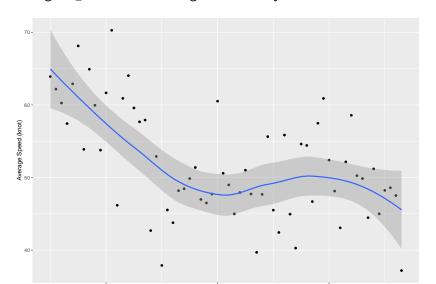


EDA - Count of Hurricanes in Each Year

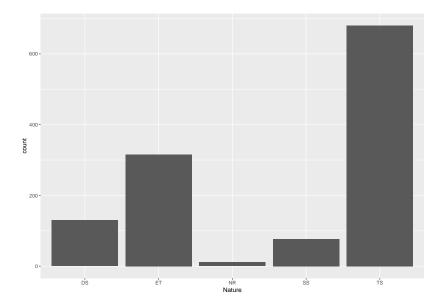


EDA - Average Speed (knot) of Hurricanes in Each Year

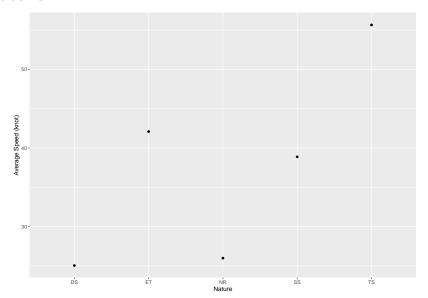
`geom_smooth()` using formula 'y ~ x'



EDA - Count of Hurricanes in Each Nature



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



Joint posterior

$$\pi(\Theta|Y)$$

$$= \pi(\mathbf{B}^{\top}, \mu^{\top}, \sigma^{2}, \Sigma \mid Y)$$

$$\propto \prod_{i=1}^{n} f(Y_i \mid \boldsymbol{\beta}_i, \sigma^2) \prod_{i=1}^{n} \pi(\boldsymbol{\beta}_i \mid \boldsymbol{\mu}, \boldsymbol{\Sigma}) P(\sigma^2) P(\boldsymbol{\mu}) P(\boldsymbol{\Sigma}^{-1})$$

$$\propto \prod_{i=1}^{n} f(Y_i \mid \beta_i, \sigma^2) \prod_{i=1}^{n} \pi(\beta_i \mid \mu, \Sigma) P(\sigma^2) P(\mu) P(\Sigma^{-1})$$

$$\propto \prod_{i=1}^{n} \left\{ (2\pi\sigma^2)^{-m_i/2} \exp\left\{ -\frac{1}{2} (Y_i - X_i \beta_i^\top)^\top (\sigma^2 I)^{-1} (Y_i - Y_i \beta_i^\top)^\top (T_i - Y$$

$$\propto \prod_{i=1}^{n} \Big\{ (2\pi\sigma^2)^{-m_i/2} \exp \big\{ -\frac{1}{2} (\boldsymbol{Y}_i - \boldsymbol{X}_i \boldsymbol{\beta}_i^\top)^\top (\sigma^2 \boldsymbol{I})^{-1} (\boldsymbol{Y}_i - \boldsymbol{X}_i \boldsymbol{\beta}_i^\top) (\boldsymbol{Y}_i - \boldsymbol{X}_i \boldsymbol{\beta}_i^\top$$

$$\times \prod_{i=1}^{n} \left\{ \det(2\pi\Sigma)^{-\frac{1}{2}} \exp\left\{ -\frac{1}{2}(\beta_i - \mu)\Sigma^{-1}(\beta_i - \mu)^\top \right\} \right\} \times \frac{1}{\sigma^2}$$

$$\times \prod_{i=1}^{n} \left\{ \det(2\pi\Sigma)^{-\frac{1}{2}} \exp\big\{ -\frac{1}{2} (\boldsymbol{\beta}_i - \boldsymbol{\mu}) \boldsymbol{\Sigma}^{-1} (\boldsymbol{\beta}_i - \boldsymbol{\mu})^\top \big\} \right\} \times \frac{1}{\sigma^2} \times$$

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.

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

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

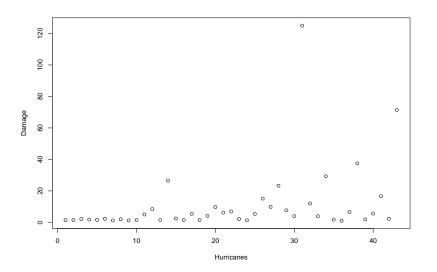
Seasonal Difference Exploration

	Beta 0		Beta 1		Beta 2		Beta 3		Beta 4	
	Estimate	Pr(> t)								
(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	-0.0033299	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

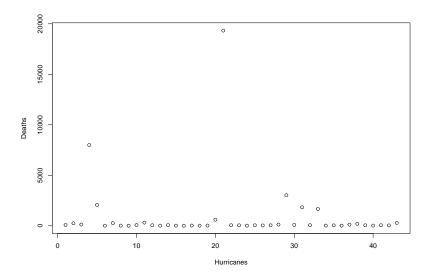
Predictions of Damage and Deaths

Basic plot of Damage and Deaths



Predictions of Damage and Deaths

Basic plot of Damage and Deaths



Coefficient table

```
## `summarise()` has grouped output by 'id', 'intercept',
##
   [1] "lid
                        intercept | beta1 | beta2
   [2] "|:----:|----:|----:
##
##
   [3] "|agnes.1972 | 3.950974| 0.9224097| 0.0059532
   [4] "|alex.2010
##
                         3.798737 | 0.9370333 | 0.0698849
##
   [5] "|alicia.1983
                         3.897408 | 0.9036878 | -0.0748341
##
   [6]
      "lallen.1980
                         3.687070 | 0.9655304 | 0.1306393
##
       "landrew.1992
                         3.676279 | 0.9375384 | -0.2843257
##
   [8]
      "|betsy.1965
                         3.808396 | 0.9513766 | -0.4500720
   [9]
      "|bob.1991
                         3.629466 | 0.9232143 |
                                             0.0279527
##
   [10] "|camille.1969
                      3.994355 | 0.9355674 |
                                             0.0729188
```

Prediction of Damage

##

```
## Call:
## glm(formula = Damage ~ ., family = "poisson", data = da-
##
## Deviance Residuals:
##
      Min
                1Q Median
                                3Q
                                        Max
## -4.4597 -1.2118 -0.4501 1.5092 4.6882
##
## Coefficients: (1 not defined because of singularities)
                  Estimate Std. Error z value Pr(>|z|)
##
## (Intercept) -2.179e+02 6.379e+01 -3.417 0.000634 *:
                5.045e+00 8.726e-01 5.781 7.41e-09 **
## intercept
                6.284e+01 1.403e+01 4.480 7.48e-06 **
## beta1
```

beta2 -1.096e+00 4.243e-01 -2.582 0.009809 **

beta3 3.378e+00 8.161e-01 4.140 3.48e-05 **

-1.393e+00 1.064e+00 ## beta4

-1.309 0.190479

nobs 4.921e-02 8.036e-03 6.124 9.15e-10 ** ## Season 7.498e-02 1.263e-02 5.938 2.89e-09 **

Prediction of Deaths

	×
(Intercept)	116.4978093
intercept	11.6747481
beta1	114.1194889
beta2	5.5287978
beta3	8.5616915
beta4	-10.4921054
nobs	0.0034309
Season	0.0061021
MonthJuly	-1.1837815
MonthJune	-1.2915971
${\sf MonthNovember}$	-2.5331919
MonthOctober	-1.5466761
MonthSeptember	-0.2751167
NatureNR	2.3487827
NatureTS	3.5634061
Maxspeed	-0.0013146
Meanspeed	_0 0367642