Tornado Analysis

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Background

- The Storm Prediction Center (SPC) rates tornado severity on the Fujita Scale (F-scale)
- F-scale rating is an integer between 0 and 5, with 5 being most severe
- Rankings are determined subjectively
- Goal: Create a method to objectively rank tornado severity based on past rankings

Data

- Information on 940 unique tornadoes in 2012 across US
- Date, time, state, property loss, crop loss, injuries, fatalities, length of impact, width of impact, beginning and ending longitude and latitude
- Reclassified state to region. Only included month out of date variables, did not include longitude and latitude

Data

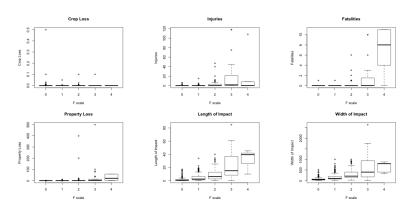


Figure: Distribution of our variables in relation to severity



Spatial Distribution

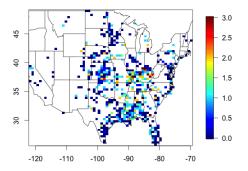


Figure: This plot shows the distribution of tornado severity in our data over the continental US

Tree Model

- Divide predictor space into T non-overlapping regions R_1, \dots, R_T
- For any $x_0 \in R_t$, make the same prediction

$$\hat{y}(x_0) = \sum_{t=1}^{T} \left(\arg \max_{c} \pi_c \right) \mathbb{1}(x_0 \in R_t)$$

Where π_c is the proportion of $\{(x_i): x_i \in R_t\}$ of class c



Growing a Tree

Find regions that minimize:

$$Error(y, \hat{y}) + \lambda T$$

- lacktriangleright λ is a tuning parameter, T is the size of the tree together they control overfitting
- \blacksquare $Error(y, \hat{y}) = Gini Index = \sum_{k=1}^{K} \hat{\pi}_{tk} (1 \hat{\pi}_{tk})$
- \blacksquare $\hat{\pi}_{tk}$ is the proportion of observations in region t of class k

Random Forests

- Trees tend to be quite variable
- Use bootstrapped samples to create 500 different trees, each time only considering m=3 (chosen by cross-validation) variables
- This decorrelates the trees and gives us better predictive accuracy
- We then average over all the trees to get our predictions (take mode)

Cross Validation for Random Forest

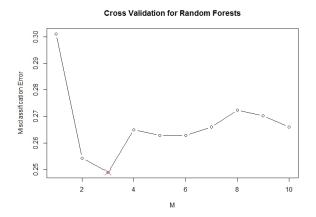


Figure: Considering 3 variables at each node minimizes error.



- Random forests help us complete our goals by allowing us to objectively predict classifications on a 0-5 integer scale for new tornadoes based on previous classifications
- Random forests don't make any assumptions, so we don't have to worry about linear/nonlinear effects

One Tree in the Forest

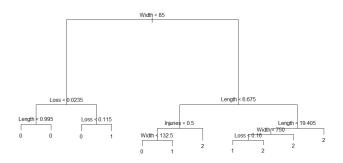


Figure: Width, Loss, Length and Injuries solely determine this tree



Classifying a New Tornado

- Obtain a classification from each tree in the forest
- Choose final classification by taking the mode of the predictions

Results

Predicted	0	1	2	3	4	Classification Error
Actual						
0	528	46	2	0	0	0.0833
1	97	128	15	1	0	0.4688
2	8	37	46	4	0	0.5157
3	0	6	13	5	0	0.7916
4	0	0	1	3	0	1.0000

Table: Random Forest Confusion Matrix

Overall Error: 232/940 = 0.2468



Results

Random Forest Covariates

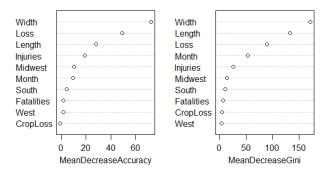


Figure: Effect if each covariate were to be left out of the tree



Conclusion

- Using random forests allowed us to classify tornadoes objectively
- Poor classification of high F-scale tornadoes due to lack of data
- Only 0 scale tornadoes are classified reliably
- Width, length and loss are the most informative covariates

Shortcomings and Further Studies

- Unable to make inference and quantify uncertainty of the effects the covariates have on F-scale rating
- Lack of wind speed data
- Better incorporate spatial effect, in the data there appears to be more of an effect than the results show
- Use spatial locations to classify tornadoes based on their likelihood to cause damage in populated areas