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Final Report:

Tropical Cyclones and the Hurricane Severity Index

Problem Statement

Since 1973 the Saffir-Simpson Hurricane Wind Scale, better known as the Saffir-Simpson Scale, has been the most widely used classification system for tropical cyclones in the Western Hemisphere aka hurricanes. While this scale does serve the purpose of classifying hurricanes based on wind speed it doesn't address a few important characteristics of tropical cyclones.

First, the scale is only able to be used for rating hurricanes – storms with maximum sustained winds of at least 64 knots (74 mph). This leaves out any rating of tropical cyclones such as tropical depressions or tropical storms, whom while having lower sustained winds can still generate destructive force on coastal areas.

The other especially important feature not captured by the Saffir-Simpson scale is the size of the storm. While wind speed alone is crucial to knowing how destructive a storm can possibly be if those winds are concentrated to a tight circumference the area affected by those winds will obviously be smaller. A larger wind field not only poses a threat to a larger area but can also have a detrimental effect on things such as wave height and storm surge as those winds travel across more surface area of the ocean exchanging more energy with the water.

In 2006 Chris Hebert and Bob Weinzapfel released a new method for measuring tropical cyclone severity named the Hurricane Severity Index (HSI). This index considers both wind speed and wind field size in order to provide a scale more representative of the destructive nature of tropical cyclones. What I have done in this project is utilize historical data in order to re-create the index. Then create multiple machine learning models that can be used to predict hurricane category and severity based on storm features.

Data Wrangling

For this project I use the HURDAT2 dataset from the National Hurricane Center (NHC). The raw dataset was rather large with 53,733 observations and 20 features and dated all the way back to 1851. I immediately decided to drop the observations predating the year 2004. This decision was made due to the fact that before 2004 there was no data for wind speed radii which is a valuable feature to the goal of calculating wind field size.

Next, I made the data more understandable by eliminating inconsistencies in the storm names and fixing the observation dates. Another key issue was with the times in which the observations were recorded. The NHC's standard to record the storm data every six hours beginning at midnight meaning the data should show observations at 0000, 0600, 1200, and 1800. Exploring the data showed 241 observations (2.9%) were at irregular times not within the NHC standard. And of those 241 observations 41.9% of them had erroneous data. This proved enough that I needed to drop any observations not within the NHC's standard recording times.

Finally, I also dropped all observations with wind speeds below 30 knots. Since 30 knots is the lower limit of the Hurricane Severity Index range any winds below this speed would not register on the scale. These changes lowered the number of observations to 5246.

EDA and Feature Engineering

After cleaning the data to a point where it is more useful, I now had to create the new features for wind field size, intensity points, size points, and total hurricane severity.

Calculating the intensity points was pretty straight forward. If the maximum wind velocity of a storm was 30 knots the storm was given 1 intensity point. If the maximum wind velocity was greater than 150 knots it was given 25 intensity points. For all maximum wind velocities in between 30 and 150 knots the intensity points were calculated by dividing the maximum wind velocity by 30 and squaring the quotient. See Formula 1 below.

$$\text{Intensity Points} = \left(\frac{Vmax}{30}\right)^2$$

Formula 1: Intensity Points

Calculating and awarding the points for size required a few more steps. I had to first figure out the field size for the four wind thresholds. The wind thresholds are 34, 50, 64, and 87 knots. For this I would have to calculate a symmetrical circle from observations measuring the furthest distance sustained winds were measured from the center of the storm for each wind speed threshold in all four quadrants of the storm. The wind field for each wind threshold was calculated using Formula 2 which takes the square root of the sum of each wind speed radius squared and multiplies it by 0.5.

$$\text{Wind Field Size} = 0.5\sqrt{(RNE^2 + RSE^2 + RSW^2 + RNW^2)}$$

Formula 2: Wind Field Size

Each wind field was then weighted based on a point range for each threshold. The point ranges are as seen in Table 1. The values for the four wind fields were each normalized to their respective point range then summed for each storm's total size points.

Wind Threshold	Point Range
34 kts	1-3
50 kts	1-4
64 kts	1-8
87 kts	1-10

Table 1: Wind Thresholds and Point Ranges

Now that the intensity points have been calculated for maximum wind speed and size points for maximum wind field size the two are added together for total hurricane severity points.

Hurricane Severity = Intensity Points + Size Points

Formula 3: Hurricane Severity Points

With the new features created, I narrowed the data down to a more concise data frame by dropping the wind radii measurements which were no longer needed. I also decreased the number of observations by taking the maximum severity, intensity, size, and wind velocity along with the lowest minimum pressure of each storm. This new data frame consists of 260 observations and 7 variables.

The new data frame contains only our most valuable consolidated data needed for exploring and modeling. The final variables for each storm include:

- **Year**: Respective year each storm occurred
- **Storm_Name**: Name given to each storm by the NHC
- **Date**: Year, month, and day the storm was strong enough to be given a name
- **Min_Pressure**: Lowest barometric pressure reading measured in millibars
- **Max_Wind**: Highest sustained wind velocity measured in knots
- **Size_pts**: 1-25 point scale created for storm size
- **Intensity_pts**: 1-25 point scale for created storm intensity

- **Severity**: 1-50 point scale created by adding Size_pts and Intensity_pts
- **Category**: The storm's highest category rank on the Saffir-Simpson Scale

In Figure 1 we can now gather a good amount of information about this data set and why there is a need for a new method for storm categorization more complex than the Saffir-Simpson Scale. As you might expect, we see more storms congregated at the lower end of the severity scale with only a few storms with a severity over 40. Hurricane Katrina is the only storm to make it to the maximum of 50 points. What is also apparent is the fairly strong correlation between barometric pressure and storm severity. As you can see as the barometric pressure decreases severity increases in a near linear fashion. The Pearson correlation between Severity and Min_Pressure is a strong -0.97.

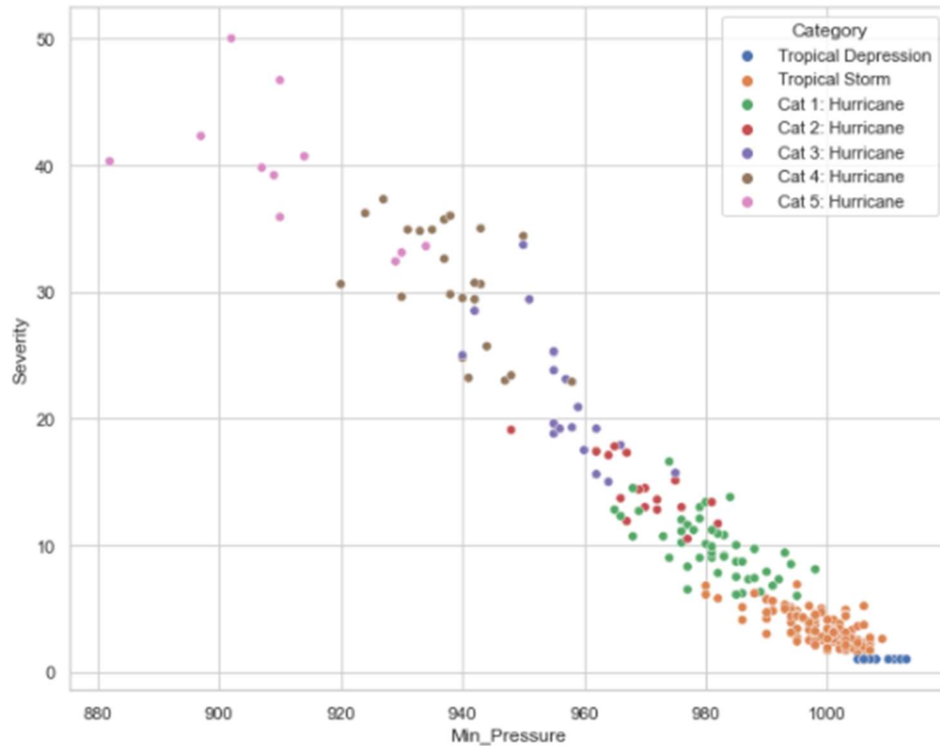

Figure 1: Minimum Pressure vs. Severity (grouped by storm category)

What is less apparent is the cross-over between storm categories with respect to severity. As you can see based on hue in Figure 1 and by reading through Table 2 some storms based only on wind speed begin to overlap categories when measuring by severity – which takes size into account as well. Take Hurricane Humberto for example. When only taking wind speed into account Hurricane Humberto would be classified as a category 3 hurricane which while still a strong hurricane might not bring as much alarm as say category 5 Hurricane Matthew. However, when taking size into account Hurricane Humberto scores higher on the severity scale than Hurricane Matthew. This is one of many examples that prove a more comprehensive system is needed for ranking tropical cyclones in the Western Hemisphere.

Year	Storm_Name	Date	Severity	Intensity_pts	Size_pts	Max_Wind	Min_Pressure	Category
2005	Katrina	2005-08-23	50.0	25.0	24.7	150.0	902.0	Cat 5: Hurricane
2004	Ivan	2004-09-03	46.7	23.4	24.7	145.0	910.0	Cat 5: Hurricane
2005	Rita	2005-09-18	42.3	25.0	20.4	155.0	897.0	Cat 5: Hurricane
2017	Irma	2017-08-30	40.7	25.0	17.7	155.0	914.0	Cat 5: Hurricane
2005	Wilma	2005-10-16	40.3	25.0	22.1	160.0	882.0	Cat 5: Hurricane
2007	Dean	2007-08-13	39.8	25.0	14.8	150.0	907.0	Cat 5: Hurricane
2017	Maria	2017-09-16	39.2	25.0	15.4	150.0	909.0	Cat 5: Hurricane
2010	Earl	2010-08-25	37.3	17.4	19.9	125.0	927.0	Cat 4: Hurricane
	Igor	2010-09-08	36.2	20.2	21.6	135.0	924.0	Cat 4: Hurricane
2004	Karl	2004-09-16	36.0	17.4	21.1	125.0	938.0	Cat 4: Hurricane
2019	Dorian	2019-08-24	35.9	25.0	16.0	160.0	910.0	Cat 5: Hurricane
2004	Frances	2004-08-25	35.7	17.4	20.2	125.0	937.0	Cat 4: Hurricane
2009	Bill	2009-08-15	35.0	14.7	21.8	115.0	943.0	Cat 4: Hurricane
2015	Joaquin	2015-09-28	34.9	20.2	15.0	135.0	931.0	Cat 4: Hurricane
2008	Ike	2008-09-01	34.9	17.4	25.0	125.0	935.0	Cat 4: Hurricane
2019	Lorenzo	2019-09-23	34.8	18.8	24.7	130.0	933.0	Cat 4: Hurricane
2016	Nicole	2016-10-04	34.4	16.0	20.6	120.0	950.0	Cat 4: Hurricane
2019	Humberto	2019-09-13	33.7	13.4	20.9	110.0	950.0	Cat 3: Hurricane
2016	Matthew	2016-09-28	33.6	23.4	13.0	145.0	934.0	Cat 5: Hurricane
2007	Felix	2007-08-31	33.1	25.0	10.2	150.0	930.0	Cat 5: Hurricane
2018	Florence	2018-08-31	32.6	18.8	18.0	130.0	937.0	Cat 4: Hurricane
2005	Emily	2005-07-11	32.4	21.8	13.8	140.0	929.0	Cat 5: Hurricane
2011	Katia	2011-08-29	30.7	16.0	16.0	120.0	942.0	Cat 4: Hurricane
2018	Michael	2018-10-07	30.6	20.2	11.3	135.0	920.0	Cat 4: Hurricane
2008	Gustav	2008-08-25	30.6	17.4	16.5	125.0	943.0	Cat 4: Hurricane

Table 2: Top 25 Storms by Severity

Machine Learning Models and Performance

With a limited number of features in my final dataset and strong collinearity between features (being multiple features were created directly from other features) I decided to keep my machine learning models basic and utilize a k-nearest neighbors (knn) model for predicting Category and a linear regression model for predicting the continuous feature of Severity. Both models will use Min_Pressure as the independent variable.

For the knn model I used Scikit-learn's KNeighborsClassifier and split the data into training and test sets of 80% and 20% respectively. Before making predictions, I tested a range of neighbors, 1 through 9, and found the most accurate number of neighbors to base predictions on to be 5.

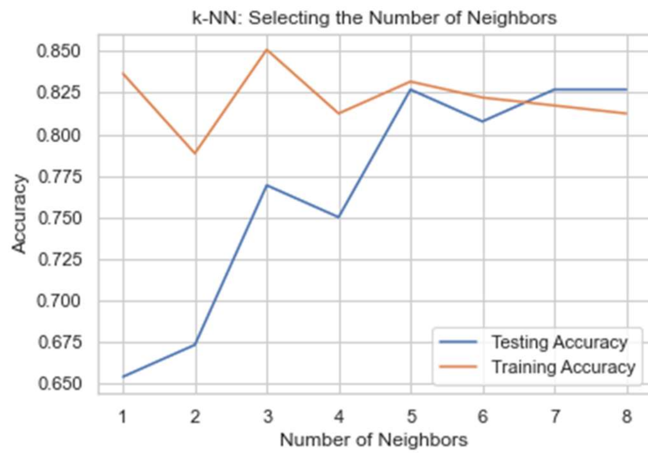

Figure 2: Neighbors Accuracy

After fitting and running the model for predictions I utilized Scikit-learn's classification_report in order to gather the statistics on the model's performance. The scores in Table 3 show the model did quite well when predicting each category as we would expect with such a strong correlation between minimum pressure and severity.

	precision	recall	f1-score	support
Cat 1: Hurricane	0.70	0.64	0.67	11
Cat 2: Hurricane	0.50	0.33	0.40	3
Cat 3: Hurricane	1.00	1.00	1.00	3
Cat 4: Hurricane	0.80	1.00	0.89	4
Cat 5: Hurricane	1.00	0.50	0.67	2
Tropical Depression	1.00	0.50	0.67	2
Tropical Storm	0.87	0.96	0.91	27
accuracy			0.83	52
macro avg	0.84	0.70	0.74	52
weighted avg	0.82	0.83	0.82	52

Table 3: k-Nearest Neighbors Classification Report

For the linear regression model, I again pulled from Scikit-learn's library and chose their LinearRegression package. I again split the data into 80% training and 20% testing sets only this time using Severity as my target. After fitting the model, I found the R-squared value of the training data at 94.2% and the Root Mean Squared Error between the test set and predicted values equal to 2.73. Figure 3 shows the regression line between actual storm severity and predicted storm severity.

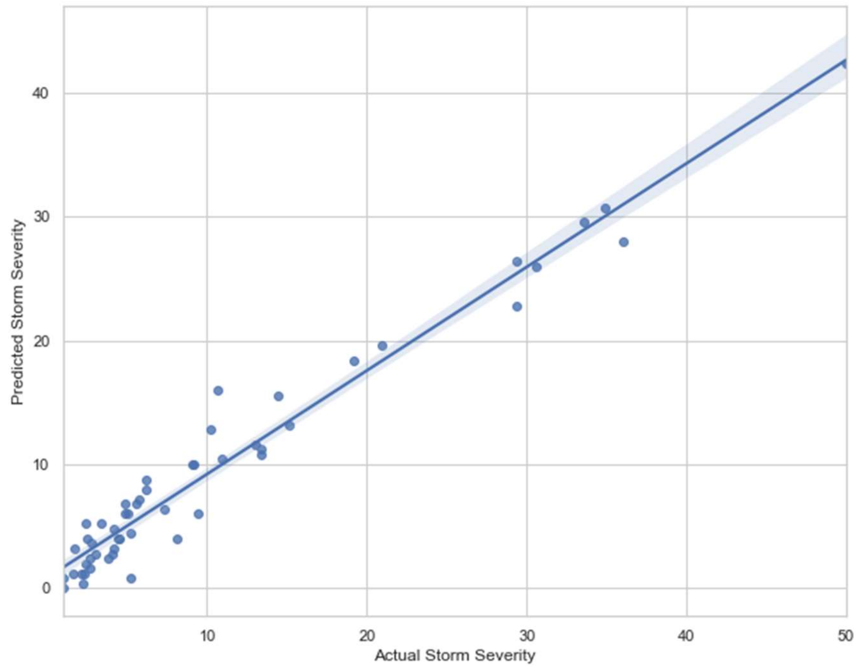

Figure 3: Actual vs Predicted Storm Severity

Lastly, using Scikit-learn's cross_val_score I ran a 4-fold cross-validation and found the model had an average cross-validation score of 93.3%.

Conclusion

Once this data set was manipulated to create new features, it helps to prove that a more complex classification method can be very useful for tropical cyclones in the future. The Saffir-Simpson Scale shows us that wind speed is a key variable in storm severity however the Hurricane Severity Index proves size also matters.

Both the k-nearest neighbors model and the linear regression model show that barometric pressure is a valuable variable when predicting the strength and severity of storms.

Future Improvements

Only using a single feature for prediction leaves plenty of room for additional features in order to make more robust models capable of possibly even more precise models. Some features I feel could be valuable include sea surface temperature, ambient air temperature, humidity levels, and possibly even jet stream location.