Predictive Agent-Based Modeling of Natural Disasters Using Machine Learning

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Abstract

Current applications of Agent-based Modeling (ABM) in natural phenomena like wildfire land suppression and hurricane forecasting are in monitoring emergent behavior patterns among large groups of people (Hilljegerdes 2018). However, current evacuation times and plans for natural disaster management leave underserved communities vulnerable to substantial financial and welfare losses, especially when false positives during current predictions continue to influence evacuation decisions. A Machine Learning ABM (ML-ABM) model of hurricane trajectories introduces a pioneering opportunity to capture complex physical processes associated with hurricanes while minimizing computational costs and errors, thereby providing more accurate real-time prediction of hurricanes for improved disaster management. This Hurricane Track Prediction ML-ABM model aims to quickly model and predict hurricane tracks in only a few minutes while retaining some of the complex physical process interactions of real storms through feature engineering and deep learning. This work focuses on the implementation of an RNN with bidirectional time-distributed Long-Short Term Memory cells[1], accounting for positive and negative time direction in time series forecasting. The observations and predictions were represented as a multi-agent system in NetLogo for further emergent pattern analysis in an expanded research by Arthur Drake et. al (2020). The model also evaluates benchmark comparisons against the National Hurricane Center's 5-Year Average Forecast Errors and the BCD5 Error Model, a combined intensity and track prediction error model that utilizes best track input and models decay over land.

Workflow

This study used IBTrACS, a National Oceanic and Atmospheric Administration (NOAA)-based data resource that combines real-time data with accurate reanalysis to provide 3-hour data increments for major storms since 1851. The applied dataset uses only points from the North Atlantic basin, main tracks, and from 2004–2020, with 2004–2016 used for

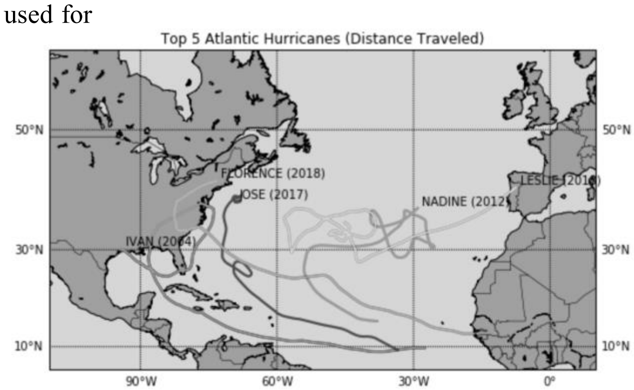

Figure 1: Top 5 Atlantic hurricanes by distance traveled showing complexities in paths traveled

training (including 5-fold cross validation) and 2017 – 2020 for evaluation. The data points were also further preprocessed to fit the appropriate data types, replace missing values, assign categorical values, and scale the features. During feature engineering, patterns emerged showing typical North Atlantic hurricane movements and complexities, as shown in Figure 1.

Methodology

The ML architecture consisted of 3 main parts: input (*X*), function (*f()),* and output *(Y*). In the architecture (Figure 1), we defined a tropical cyclone record at each timestep (*i*), i.e., $tc_i = (lat_{i,t0}, lon_{i,t0} F_{i,t0} \dots lat_{i,t5}, lon_{i,tn}, F_{i,tn})$, with F representing all other input features (ISO time, maximum sustained wind, minimum central pressure, and wind radii across 4 quadrants), and $n = 5$. These features

[1] Usmani, H. 2018. hurricane-net. github.com/hammad93/hurricane-net. Accessed July 2020.

were reshaped, scaled according to the quartile range, and fitted to the network a multivariate regression model, $\hat{Y} = b_{i,t0} + b_{i,t1}, X_{i,t1} + b_{i,t2}X_{i,t2} + \ldots + b_{i,n}X_{i,tn}$ where $\hat{Y}$ represents predicted values (latitude, longitude, and wind intensity) of $X_1 \ldots X_n$, $b_{i,t0}$ the value when $X_1 \ldots X_n$ equal zero, and $b_{i,t1} \ldots b_{i,tn}$ the estimated regression coefficients.

The results were iterated and adjusted through a feedback loop, evaluated using a Mean Squared Error loss function, and final outputs made to stand as our predicted storm measurements. The predictions were translated into physical measurements (nautical miles for distance and knots for wind intensity) in terms of averaged errors in the 5 timesteps (24-hour intervals of the 5-day forecast).

Results and Discussion

This ABM-ML model performed highly, as follows: wind intensity accuracy was 73.7%, latitude and longitude accuracy 85.3%. Further comparisons to the NHC BCD5 Track Error and Wind Intensity models are +187 nautical miles for distance predictions per our model and +2 knots for per our wind intensity predictions. Storm predictions and interpretations are shown in Figure 2, across the 5-Day Forecast model.

Aiming to link other parameters to the storm's overall movement direction and speed, several correlations were explored among the data's features. Storm direction exhibited a moderate positive correlation with strongest wind direction. However, movement speed exhibited no meaningful correlations within the dataset. A measure of average acceleration in prior time-steps is useful for gauging short-term changes in velocity.

Overall, the direction correlation may be quite useful in an augmented ABM decision tree (for example, after landfall), as it has potential to correct some of the biases of the initial RNN results. Figure 3 depicts an error plot for Hurricane Arthur's trajectory predictions.

Average Intensity & Average Distance Errors

Timestep (hrs)	24	48	72	96	120
Intensity (kts)	21	22	23	24	25
Distance (n. miles)	223	458	575	779	1155

Figure 2: Predicted storm measurements using augmented ML architecture

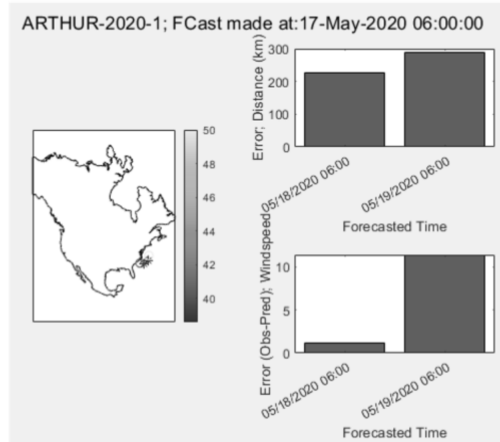

Figure 3: Error plot for Hurricane Arthur (2020), comparing predicted and real trajectory and windspeed measurements

Conclusion

Machine Learning Agent-Based Modeling enables faster and more accurate disaster relief management to address crucial rising concerns about the impact of global warming. This would enable better allocation of emergency disaster relief resources to ensure the safety of people and make programs more inclusive. To better capture the distinct micro-interactions at each cell and create a dynamic predictive system, Voronoi Diagrams, as an Agent-based model, can be integrated with a predictive element to evaluate continuous values that represent spatial boundaries in simulations.

References

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