

Predicting Hurricane Trajectories using a Recurrent Neural Network

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Abstract

Hurricanes are cyclones circulating about a defined center whose closed wind speeds exceed 75 mph originating over tropical and subtropical waters. At landfall, hurricanes can result in severe disasters. The accuracy of predicting their trajectory paths is critical to reduce economic loss and save human lives. Given the complexity and nonlinearity of weather data, a recurrent neural network (RNN) could be beneficial in modeling hurricane behavior. We propose the application of a fully connected RNN to predict the trajectory of hurricanes. We employed the RNN over a fine grid to reduce typical truncation errors. We utilized their latitude, longitude, wind speed, and pressure publicly provided by the National Hurricane Center (NOAA) to predict the trajectory of a hurricane at 6-hour intervals.

1 Introduction

Hurricanes are thermally driven, large-scale cyclones whose wind speeds exceed 75 miles per hour and circulate about a well-defined center [Miller, 1967]. They arise from the warm waters of the Atlantic Ocean and the Caribbean Sea and typically travel North, Northwest, or Northeast from their point of origin. Hurricanes' nature of having strong winds, heavy precipitation, and dangerous tides typically result in severe economic disasters and loss of lives. In 1965 Hurricane Betsy caused \$1.5 billion of property damage at Florida and the Gulf States [Miller, 1967]. In 2005, Hurricane Katrina resulted in 853 recorded fatalities also in regions of Florida [Jonkman *et al.*, 2009]. The prediction of hurricane trajectories allows for civilians to properly evacuate and prepare for these dangerous and destructive storms. Hurricane track forecasting is not simple, however, as hurricanes are highly erratic in their movements.

The development of current seasonal hurricane forecast methods has advanced over the past decades. However, most of the current hurricane trajectory forecast methods are statistical in nature [Wang *et al.*, 2009]. These statistical approaches are limiting due to the complexity and nonlinearity of atmospheric systems. Recurrent neural networks (RNNs) have been recently used to forecast increasingly complicated systems. RNNs are a class of artificial neural networks where

the modification of weights allows the model to learn intricate dynamic temporal behavior. An RNN with the capability of efficiently modeling complex nonlinear temporal relationships of a hurricane could increase the accuracy of predicting future hurricane path forecasts. Development of such an approach is the focus of this paper.

While others have used RNNs in the forecasting of weather data, to our knowledge this is the first fully connected recurrent neural networks employed using a grid model for hurricane trajectory forecasts. The proposed method can more accurately predict trajectories of hurricanes compared to traditional forecast methods employed by the National Hurricane Center (NHC) of the National Oceanic and Atmospheric Administration (NOAA). This paper summarizes our present state of model development. After reviewing the related work and background of recurrent neural networks, we describe in detail the elements of our proposed approach. Subsequently, we compare our results with the real trajectories of randomly selected hurricanes: ALEX, DELTA, SANDY, HORTENSE, IVAN, and PALOMA.

2 Related Work

Scientists are interested in improving the capability of predictive models for tracking hurricanes for the safety of individuals. There exist various forecast prediction models for the tracking of hurricanes. The present-day models vary immensely in structure and complexity. The National Hurricane Center (NHC) of the National Oceanic and Atmospheric Administration (NOAA) uses four main types of models in their path predictions: dynamical, statistical, statistical-dynamical, and ensemble or consensus models.¹

Dynamical models, or numerical models, are complex as they require the highest computational power to process physical equations of motion in the atmosphere. Kurihara *et al.* describe a dynamical model called the Geophysical Fluid Dynamics Laboratory (GFDL) Hurricane Prediction System that was created to simulate hurricanes [Kurihara *et al.*, 1998]. This model created a multiply nested movable mesh system to generate the interior structure of a hurricane and used cumulus parameterization to successfully generate a real hurricane. The GFDL model can be divided into four phases:

¹NHC Track and Intensity models provided at: <https://www.nhc.noaa.gov/modelsummary.shtml>

(1) establish a global model forecast onto grid points of the hurricane model, (2) initialize model through the method of vortex replacement, (3) execute model to create a 72-hour prediction, and (4) provide time series information containing storm location, minimum pressure, maximum wind distribution, a map of the storm track and the time sequences of various meteorological fields [Kurihara *et al.*, 1998].

Statistical models are light-weight models which only use statistical formulas to discover storm behavior relationships from historical data. The relationships utilized to predict hurricane trajectories are based on many storm-specific features collected, such as location and date of the hurricane. In [Hall and Jewson, 2007], the statistical non-parametric model derives simulations of possible trajectory paths by spatially averaging historical data. This method strives to avoid overfitting with the maximal amount of historical data by using out-of-sample validation to optimize data averaging. Dynamical systems combined with the statistical relationships allow for models to employ large-scale variables as a set of predictors for hurricane forecast schemes. In [Wang *et al.*, 2009], they utilized a statistical-dynamical model to predict the trajectory paths of hurricanes in the Atlantic based on the relationship between variability of hurricane trajectories, sea surface temperatures, and vertical wind shear.

Ensemble or consensus models are a combination of forecasts from different models, different physical parameters, or varying model initial conditions. These models have shown to be more accurate than the predictions from their individual model components on average [Krishnamurti *et al.*, 2000]. However, there are still many challenges associated with modeling nonlinear spatiotemporal systems and as a result, many of the statistical developments have been left behind by disciplines such as machine learning. In [Lee and Liu, 2000], data mining techniques are used to predict the features of hurricanes as it provides a time-series analysis. However, this feed-forward attempt of applying machine learning to nonlinear spatiotemporal processes does not capture time-sequential dynamical interactions between variables of natural events [McDermott and Wikle, 2017].

In [Moradi Kordmahalleh *et al.*, 2016], sparse Recurrent Neural Network with a flexible topology is used where the weight connections are optimized using a Genetic Algorithm (GA). It accumulates the historical information about dynamics of the system and uses at the time of prediction. Dynamic Time Warping (DTW) is used to make all the hurricanes uniform, allowing the Recurrent Neural Network to equally learn from each hurricane. However, the use of DTW in this model does not allow for hurricanes whose path is not monotonic. In other words, hurricanes that turn back on itself are not considered. Due to the stochastic nature of hurricane trajectories, Recurrent Neural Networks could benefit from learning from all hurricane paths. Therefore, the accuracy of hurricane trajectory forecasts could benefit from a Recurrent Neural Network that could model the temporal behaviors of a due to the complexity and nonlinearity of the atmospheric systems.

Due to the complexity and non-linearity of the atmospheric systems and lack of using available hurricane observations, there is a need for networks with the capability of modeling the temporal behaviors of a hurricane. With the high com-

plexity and continuously increasing the quantity of data collected, linear models are limiting. A recurrent neural network with the capability of modeling any complex nonlinear temporal behaviors of a hurricane could increase the accuracy of predicting future hurricane trajectories.

3 Recurrent Neural Networks

Recurrent Neural Networks (RNNs) are nonlinear dynamical models commonly used in machine learning to represent complex dynamical or sequential relationships between variables [McDermott and Wikle, 2017]. Dynamical spatiotemporal processes, such as forecasting hurricane trajectories, represent a class of complex systems that can potentially benefit from RNNs. Similar dynamical spatiotemporal processes have benefited greatly from the application of RNNs [Maier and Dandy, 2000; Barbounis *et al.*, 2006].

RNNs are generally fully connected networks, where connection weights are the training parameters. A simple architecture of a deep recurrent neural network arranges hidden state vectors h_t^l in a two-dimensional grid, where $t = 1, \dots, T$ is the total time the neural network will learn and $l = 1, \dots, L$ is the depth of the network. Figure 1 shows a simple RNN architecture with a depth of two.

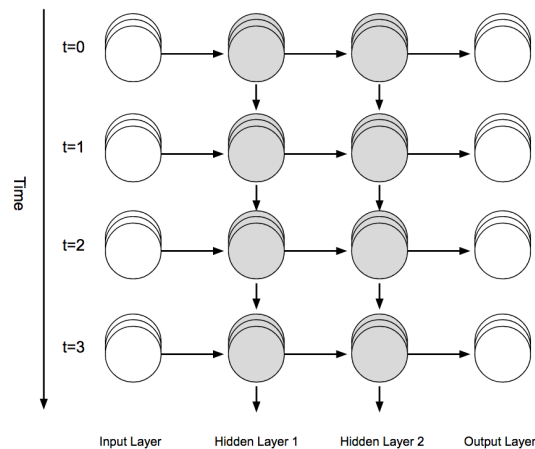


Figure 1: Sample Simple Recurrent Neural Network Architecture

The n_y -dimensional vector output Y_t corresponding to the original n_x -dimensional vector input X_t is given by:

$$Y_t = g(V^l * h_t^L) \quad (1)$$

where h_t^L is the final n_h -dimensional vector of hidden state variables that is used to predict the output vector, V^l is the $n_y \times n_h$ weight matrix, and the function $g(\cdot)$ is an activation function that creates the mapping between the output and the hidden states. The hidden state vectors h_t^l are defined by:

$$h_t^l = f(W^l * h_{t-1}^l + U^l * X_t) \quad (2)$$

where W^l is a $n_h \times n_h$ weight matrix, U^l is a $n_h \times n_x$ weight matrix, and the function $f(\cdot)$ is the activation function for the hidden layers [Karpathy *et al.*, 2015]. The activation function $f(\cdot)$ construes the output and is one of the core components

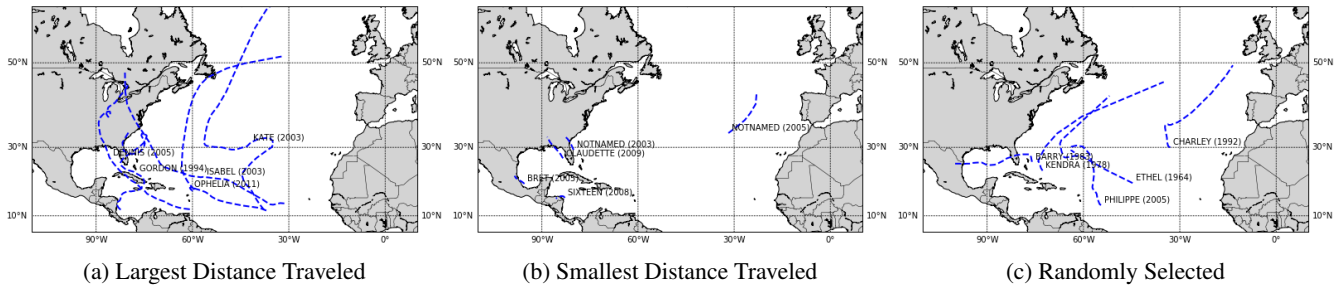


Figure 2: 15 Atlantic Hurricane Trajectories Collected by Unisys Weather²

of the neural network architecture [Tong and Mintram, 2010]. The nonlinearity of the RNN model is influenced by these activation functions. The weight matrix W models underlying dynamic connections between the various hidden states. Thus, latent nonlinear interactions can effectively be modeled within this framework through W . Hidden states extract and provide notable hidden dynamic features from the data and allow the V parameters to appropriately weight these patterns [McDermott and Wikle, 2017]. Making recurrent neural networks appropriate and effective at modeling and forecasting the complex atmospheric systems of hurricanes.

4 Hurricane Data

The raw Atlantic hurricane/tropical storm data used in the study were extracted from the NOAA database.² The data contains all hurricanes and tropical storms from 1920 to 2012. It includes the 6-hourly center locations (latitude and longitude in tenths of degrees), as well as the wind speed (in knots where one knot is equal to 1.15 mph) and minimal central pressure (in millibars) for the life of the historical track of each cyclone. Tropical storms are cyclones whose wind speeds do not exceed 75mph. These were considered in our model as the behavior of tropical storms are the same as those of fully-developed hurricanes and provides insight on trajectory behavior. The trajectories of several of the storms from the database are depicted in Figure 2.

We utilized the hurricane points with valid longitude, latitude, wind speed, and pressure values. Figure 3 contains the number of hurricanes that had tuple quantities varying from 7 to 59 where the 50th percentile of hurricanes contained 21 data points collected in its lifespan. The RNN learning was performed mostly on hurricanes with duration of 126 hours.

The distance traveled and angle of travel, or direction, was extracted from the latitude and longitude values of each point collected 6-hourly by each hurricane. These augmented parameters allow the neural network to learn about relative rather than absolute parameters. Relative variables provide a measure of relation and representation learning for unseen paths. From the set of hurricanes we are utilizing, the largest hurricane, Hurricane Kate (2003), traveled approximately 6394.7 miles while the smallest hurricane, Hurricane Edouard (1984), traveled approximately 86.5 miles. Al-

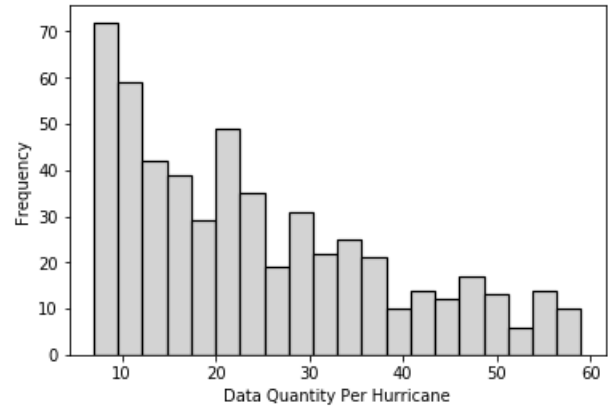


Figure 3: Amount of Hurricanes per Data Quantity

though not explicitly given by the original dataset, we can conclude the direct correlation between the number of data points collected per historical track and the total distance traveled by what is shown in Figure 4. From this, we can also conclude that hurricanes are continuously traveling.

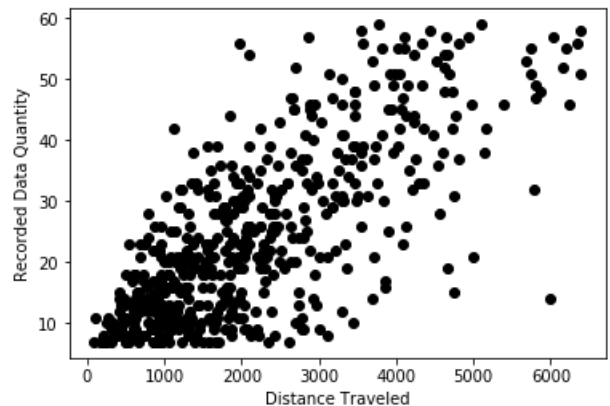


Figure 4: Recorded Data Quantity vs. Distance Traveled

Using direction and angle of travel as influencing features in our model, the values were normalized to ensure the values of each hurricane were centered around a normal distribution with invariant mean and variances. It has

²Atlantic hurricane tracking by year provided at: <http://weather.unisys.com/hurricane/atlantic/>

been shown that RNN with normalized data learns from every input equally, generalizing better and converging significantly faster [Cooijmans *et al.*, 2016]. It does so as RNN returns more confident results when learning within the interval [0,1] while being more conservative in its sample. Normalizing is completed using $Z = \frac{X-\mu}{\sigma}$ where X is the original value, Z is the normalized value, μ and σ are the mean and standard deviation of all the values collected by a historical hurricane path, respectively. A normalized value represents the probability that the value could appear in the given historical data, therefore the RNN can modify the weight vectors at each state easily shown by a runtime speedup of the RNN training [Witten *et al.*, 2016; Cooijmans *et al.*, 2016]. The distance and angle distributions are given by Figure 5.

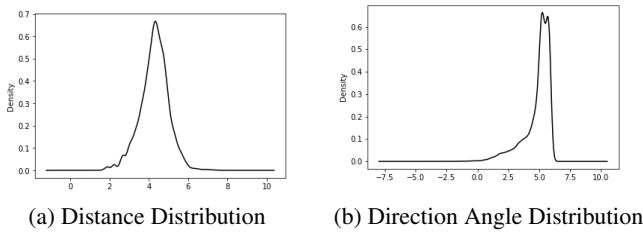


Figure 5: Augmented Parameter Distributions

5 Model and Implementation

In this paper, hurricane forecasting is performed by a fully-connected RNN employed over a grid system. The proposed network has the capability to accumulate the historical information about the nonlinear dynamics of the atmospheric system by updating the weight matrices appropriately. This capability makes the RNN suitable for modeling the complex system of hurricane behavior with unobservable states.

5.1 Grid Model

We trained our neural network to learn about a grid model, meaning that the RNN will learn the behavior of a hurricane trajectory moving from one grid location to another. Typical numerical methods contain truncation errors due to computational limitations. As numerical models attempt to increase accuracy and reduce the scale, truncation errors become more excessive [Birchfield, 1960]. If minor truncation errors propagate throughout the prediction, this could represent hundreds of miles in potential error. Employing the grid system and reducing the number of possible truncation errors contributes to the improved accuracy of our model by allowing us to control the amount of loss used by prediction.

Figure 6 shows the recorded latitude and longitude points collected by Unisys Weather Data used to train and test our model. This figure allows us to see the habitual behavior of hurricane trajectories given certain atmospheric information. By placing a refined grid over the latitude and longitude points, truncation errors are reduced while allowing for a larger scale model that encapsulates the small-scale features more clearly accurately [Birchfield, 1960]. This being

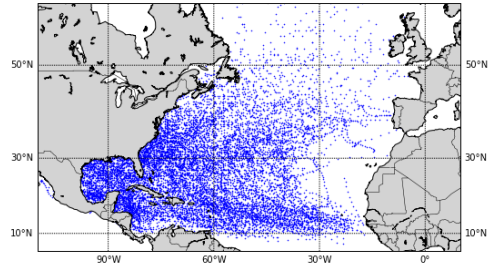


Figure 6: Atlantic Hurricane Points Collected by Unisys Weather²

an ideal arrangement for RNNs to optimally grasp the complexity of hurricane trajectories.

5.2 Main RNN Hyperparameters

Commonly required by many machine learning algorithms, hyperparameters are preset values optimally selected by the programmer before training begins. The activated values of hyperparameters vary greatly depending on the model being employed, the quantity and quality of the data being used, and the complexity of the model. These hyperparameters are fundamental in encapsulating the nonlinearly and complexity behind forecasting hurricane paths as they influence the decision making steps when updating the weight matrices.

Dropout

A regularly used hyperparameter, known as the dropout value, randomly ignores a percentage of the input to prevent the model from co-adapting to the training set, or overfitting, of hurricane trajectories [Srivastava *et al.*, 2014]. This value was set to 0.1 and was tuned and selected using cross-validation, meaning 10% of each input was ignored when training our RNN.

Grid Boundaries

The number of grid blocks in our model could be tuned depending on the amount of hurricane data available. The number of grid blocks optimal for the RNN is directly proportional to the number of data points available to train on. Given that we utilized 13131 total valid data points and 539 hurricane/tropical storm trajectories, we utilized a total of 7256 grid blocks. The grid blocks were of size 1x1 degrees latitude by longitude. Due to the spherical nature of Earth, the area of each grid block is not uniform in square miles but since most points are centered around Earth's equator, the difference in size for each grid block is negligible.

Hidden State Vectors

Hidden state vectors, often referred to as hidden layers, isolate notable hidden dynamic features from the input data. The number of hidden layers in RNNs contribute to the complexity of the model. It has been shown that having at least two hidden state vectors returns satisfactory results, but more than three hidden state vectors do not provide significant improvement: increasing the hidden layers, given there are more than three, tends to overfit [Karpathy *et al.*, 2015]. Therefore, we employed three hidden layers each with a long short-term memory cell to properly encapsulate the complexity of hurricane trajectory behavior while not overfitting.

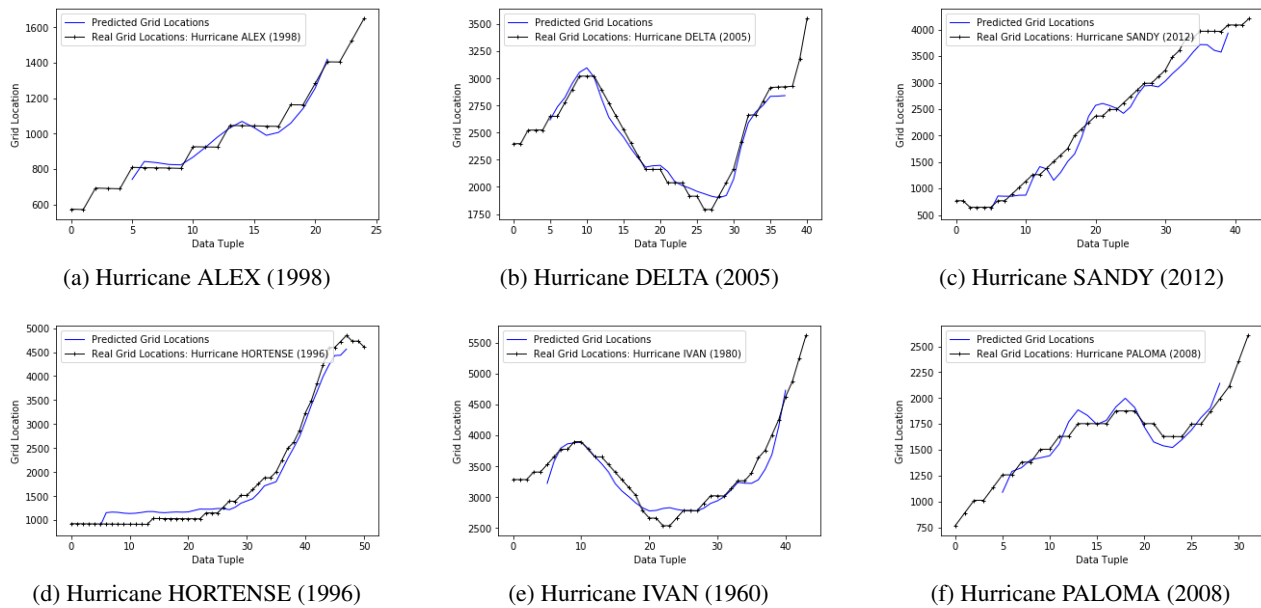


Figure 7: Randomly Selected Atlantic Hurricane Trajectory Predictions

Long Short-Term Memory Cell

Long Short-Term Memory Cells (LSTM) are a building unit for layers in RNNs. The main purpose of these cells is to remember values over arbitrary time intervals by preventing vanishing and exploding weights throughout the RNN. As a result, LSTMs have shown to provide a significant improvement in RNN performance when applications require long-range reasoning [Karpathy *et al.*, 2015]. There exists other variants of LSTM for RNNs with the same intentions; however, LSTM was the most successful in storing and retrieving information over long periods of time [Karpathy *et al.*, 2015]. As hurricane trajectories can span over hundreds of hours, these long-term cells in the hidden layers positively contribute to the RNN’s ability to learn about each hurricane.

5.3 Implementation

For the implementation of our model, we utilized Keras. Keras is an API that integrates with lower-level deep learning languages such as TensorFlow. It has been increasingly used in the industry and research community with over 200,000 individual users as of November 2017 and large scientific organizations including CERN and NASA³. This API provided a sequential recurrent neural network model with input, hidden, and output layers created with the necessary parameters to facilitate the process of creating the RNN.

Keras provides a default learning rate hyperparameter of the value 0.001. The learning rate is the rate at which the RNN when updating the weights using Stochastic Gradient Descent at each hidden layer [Chung *et al.*, 2014]. The learning rate is used to minimize the error and stabilize the process of updating the weight matrices. Our model also utilized the activation function hyperbolic tangent rather than the frequently used sigmoid and rectified linear unit functions. This

is so as this activation function allowed the model to output values between $[-1, 1]$ which better models movement in all directions. The model was trained on an NVIDIA GeForce GTX 1060 with 6GB of RAM which allowed the model to complete training in 200 seconds.

6 Forecast Results

The accuracy of our RNN employed over a grid system is shown for the trajectory predictions of the powerful hurricanes such as ALEX, DELTA, SANDY, HORTENSE, IVAN, and PALOMA. Figure 7 shows the forecasted trajectory grid locations of these randomly selected hurricanes. Of these selected hurricanes, Hurricane SANDY was the deadliest, most destructive, and costliest hurricane. Due to its excessive wind field, large storm surge, and unusual track into the population-dense area, the damage was about \$75 billion [Force, 2013]. Thousands of business were damaged or forced to close in addition to the 650,000 homes that were damaged or destroyed. At least 159 people were killed along the path of the storm.

The data provided by Unisys Weather data was divided where 85% of the total hurricanes were used for training, and 15% were used for testing the accuracy of our model. The six hurricanes shown in Figure 7 were not storms contained in the training set, meaning our RNN had not seen any of these specific hurricane paths during the training phase. When the RNN is deriving a model to predict nonlinear and complex systems, predictive quantification and validity is essential when testing on a dataset different from the training dataset [Ivanescu *et al.*, 2016]. As a result, validation of the training set was completed on 10% of the 85% training set. At the time of testing, hurricanes were fed into the RNN one hurricane, or tropical storm, at a time. The predicted grid locations path, shown on Figure 7, are shorter than the real grid location path as the first prediction is made after 5 6-hourly

³Keras API: <https://keras.io/layers/recurrent/>

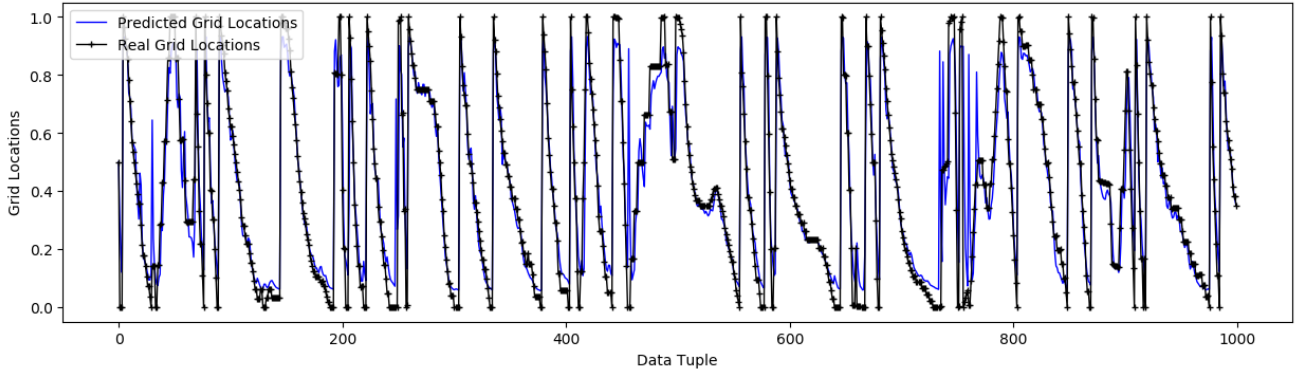


Figure 8: Hurricane Predictions for All Data Tuples

times steps, or 30 hours total. One can see that the RNN was able to successfully encapsulate, model, and forecast the future trajectory paths of hurricanes at 6 hour intervals.

As was stated in Section 2, the sparse Recurrent Neural Network with a flexible topology was trained and tested using the Unisys Weather dataset. This method, although presented impressive results, lacks in modeling and forecasting hurricane behaviors that occur frequently in nature. Due to their use of DTW, they are unable to train or test on hurricanes that contain loops. In Table 1, we compare the Mean Absolute Error (MAE) results they presented with the MAE results of scaled values we predicted. The methods referred to in the related work are not open source and are difficult to reproduce, we compared with [Moradi Kordmahalleh *et al.*, 2016] as they used the same dataset. However, their predictions were in the form of latitude and longitude with a calculated MAE for each. Our method which employed the grid system returns grid locations as converting back to trajectory paths reduces accuracy. The MAE calculated between the scaled predicted grid block value and the real grid block value. Our grid boundaries are located at a 1x1-degree scale to latitude and longitude. As a result, these two methods can be compared from the provided MAE values, though we note that we are comparing errors with respect to grid block values for our approach vs. errors over the latitude and longitude values for the sparse RNN approach. The most appropriate comparison from the table is between the Grid-Based RNN MAE and the average of latitude and longitude MAE for sparse RNN. We can clearly see that our method properly encapsulated the nonlinearity and complexity of hurricane trajectories.

Hurricane	DEAN	SANDY	ISAAC
Grid-Based RNN	0.0842	0.0800	0.0592
Sparse RNN Latitude	0.8651	0.2500	0.7888
Sparse RNN Longitude	0.0572	0.5949	0.3425
Sparse RNN Average	0.46115	0.42245	0.56565

Table 1: Mean absolute error using our grid-based approach and the sparse RNN approach. Errors of our approach are with respect to the grid created from the latitude and longitude data while the sparse RNN errors are with respect to the direct latitude and longitude data.

7 Conclusion

We proposed a recurrent neural network employed over a grid system with the intention to encapsulate the nonlinearity and complexity behind forecasting hurricane trajectories and potentially increasing the accuracy compared to operating hurricane track forecasting models. Our model predicts the next hurricane location 6-hourly, as the hurricane points are collected by Unisys Weather data with this time frequency. Figure 8 contains the normalized comparison between the real and predicted grid locations for all trained and tested data tuples. These values are the exact output values of our RNN and returned a 0.01 mean-squared error (0.11 root-mean-squared error) for both the training and testing set.

We compared our results with a sparse RNN that forecasted hurricane behavior. We compared to their method using mean absolute error, and from Table 1 we can see that we had superior results. Improved accuracy of our model is due to the extracted parameters direction, or angle of travel, and distance. These relative parameters employed over the grid system allow for the RNN to learn behavior rather than absolute latitude and longitude coordinates. Also, the sparse RNN only trained and tested on monotonic hurricanes, or hurricanes that do not turn back on themselves or contain loops. As a result, this model does not accurately imitate hurricane behavior as many hurricanes contain loops in their tracks, for example, Hurricane IVAN. Overall, our proposed grid-based RNN was able to accurately learn, model, and forecast hurricanes with any given trajectory path by adequately encapsulating the nonlinearity and complexity in atmospheric systems.

Our model’s final results were grid location prediction coordinates (rather than latitude and longitude) with high accuracy, as shown in Figure 8. However, when we extract individual hurricane trajectories from grid locations and converting to latitude and longitude coordinates accuracy is decreased. In future work, we will explore the application of an artificial neural network to properly and accurately convert from grid locations to latitude-longitude coordinates. In addition, the application of a Bayesian neural network in combination with our grid-based RNN could increase accuracy as Bayesian models could quantify the uncertainty of a prediction. This uncertainty parameter is also valuable information in hurricane trajectory predictions.

References

- [Barbounis *et al.*, 2006] Thanasis G Barbounis, John B Theocharis, Minas C Alexiadis, and Petros S Dokopoulos. Long-term wind speed and power forecasting using local recurrent neural network models. *IEEE Transactions on Energy Conversion*, 21(1):273–284, 2006.
- [Birchfield, 1960] Gene E Birchfield. Numerical prediction of hurricane movement with the use of a fine grid. *Journal of Meteorology*, 17(4):406–414, 1960.
- [Chung *et al.*, 2014] Junyoung Chung, Çağlar Gulcehre, KyungHyun Cho, and Yoshua Bengio. Empirical evaluation of gated recurrent neural networks on sequence modeling. *arXiv preprint arXiv:1412.3555*, 2014.
- [Cooijmans *et al.*, 2016] Tim Cooijmans, Nicolas Ballas, César Laurent, Çağlar Gülçehre, and Aaron Courville. Recurrent batch normalization. *arXiv preprint arXiv:1603.09025*, 2016.
- [Force, 2013] Hurricane Sandy Rebuilding Task Force. Hurricane sandy rebuilding strategy. *US Department of Housing and Urban Development, Washington DC*, 2013.
- [Hall and Jewson, 2007] Timothy M Hall and Stephen Jewson. Statistical modelling of north atlantic tropical cyclone tracks. *Tellus A*, 59(4):486–498, 2007.
- [Ivanescu *et al.*, 2016] Andrada E Ivanescu, Peng Li, Brandon George, Andrew W Brown, Scott W Keith, Dheeraj Raju, and David B Allison. The importance of prediction model validation and assessment in obesity and nutrition research. *International journal of obesity*, 40(6), 2016.
- [Jonkman *et al.*, 2009] Sebastiaan N Jonkman, Bob Maaskant, Ezra Boyd, and Marc Lloyd Levitan. Loss of life caused by the flooding of new orleans after hurricane katrina: analysis of the relationship between flood characteristics and mortality. *Risk analysis*, 29(5):676–698, 2009.
- [Karpathy *et al.*, 2015] Andrej Karpathy, Justin Johnson, and Li Fei-Fei. Visualizing and understanding recurrent networks. *arXiv preprint arXiv:1506.02078*, 2015.
- [Krishnamurti *et al.*, 2000] Tiruvalam Natarajan Krishnamurti, CM Kishtawal, Zhan Zhang, Timothy LaRow, David Bachiochi, Eric Williford, Sulochana Gadgil, and Sajani Surendran. Multimodel ensemble forecasts for weather and seasonal climate. *Journal of Climate*, 13(23):4196–4216, 2000.
- [Kurihara *et al.*, 1998] Yoshio Kurihara, Robert E Tuleya, and Morris A Bender. The gfdl hurricane prediction system and its performance in the 1995 hurricane season. *Monthly weather review*, 126(5):1306–1322, 1998.
- [Lee and Liu, 2000] Raymond ST Lee and James NK Liu. Tropical cyclone identification and tracking system using integrated neural oscillatory elastic graph matching and hybrid rbf network track mining techniques. *IEEE Transactions on Neural Networks*, 11(3):680–689, 2000.
- [Maier and Dandy, 2000] Holger R Maier and Graeme C Dandy. Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications. *Environmental modelling & software*, 15(1):101–124, 2000.
- [McDermott and Wikle, 2017] Patrick L McDermott and Christopher K Wikle. Bayesian recurrent neural network models for forecasting and quantifying uncertainty in spatial-temporal data. *arXiv preprint arXiv:1711.00636*, 2017.
- [Miller, 1967] Banner I Miller. Characteristics of hurricanes: Analyses and calculations made from measurements by aircraft result in a fairly complete description. *Science*, 157(3795):1389–1399, 1967.
- [Moradi Kordmahalleh *et al.*, 2016] Mina Moradi Kordmahalleh, Mohammad Gorji Sefidmazgi, and Abdollah Homaifar. A sparse recurrent neural network for trajectory prediction of atlantic hurricanes. In *Proceedings of the Genetic and Evolutionary Computation Conference 2016*, pages 957–964. ACM, 2016.
- [Srivastava *et al.*, 2014] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. Dropout: A simple way to prevent neural networks from overfitting. *The Journal of Machine Learning Research*, 15(1):1929–1958, 2014.
- [Tong and Mintram, 2010] Dong Ling Tong and Robert Mintram. Genetic algorithm-neural network (gann): a study of neural network activation functions and depth of genetic algorithm search applied to feature selection. *International Journal of Machine Learning and Cybernetics*, 1(1-4):75–87, 2010.
- [Wang *et al.*, 2009] Hui Wang, Jae-Kyung E. Schemm, Arun Kumar, Wanqiu Wang, Lindsey Long, Muthuvel Chelliah, Gerald D. Bell, and Peitao Peng. A statistical forecast model for atlantic seasonal hurricane activity based on the ncep dynamical seasonal forecast. *Journal of Climate*, 22(17):4481–4500, 2009.
- [Witten *et al.*, 2016] Ian H Witten, Eibe Frank, Mark A Hall, and Christopher J Pal. *Data Mining: Practical machine learning tools and techniques*. Morgan Kaufmann, 2016.