PREDICTING HURRICANE TRAJECTORIES USING A RECURRENT NEURAL NETWORK

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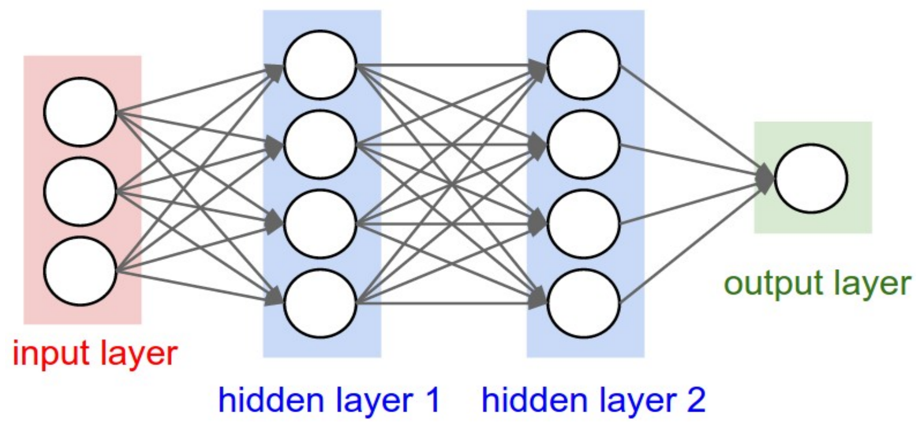
WHAT ARE NEURAL NETWORKS?

- Neural networks are a model used in machine learning and have been applied to speech and object recognition, and natural language processing [1].
- The figure below contains a simple neural network example. Each circle is called a "neuron" and these neurons send each other information.
- The inputs and outputs adjust these connections (or weights). They are adapted to reach the most optimal output value.
- This adjustment of weights is completed using forward and backward propagation.



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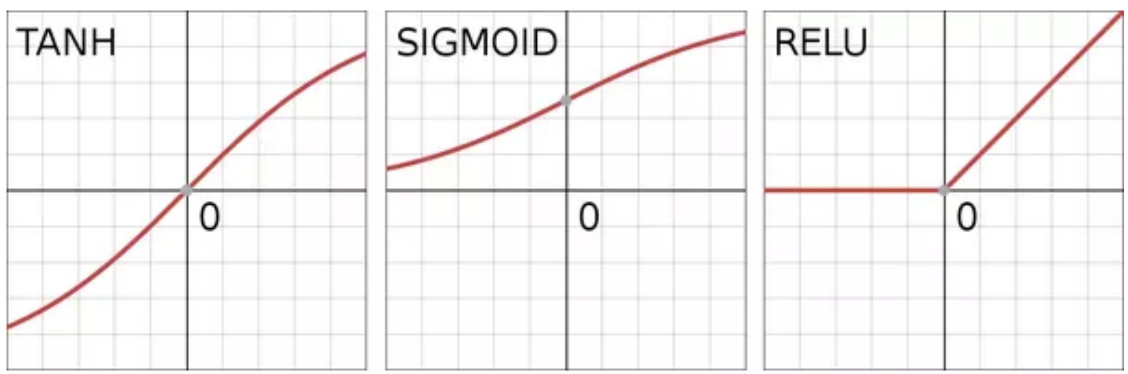
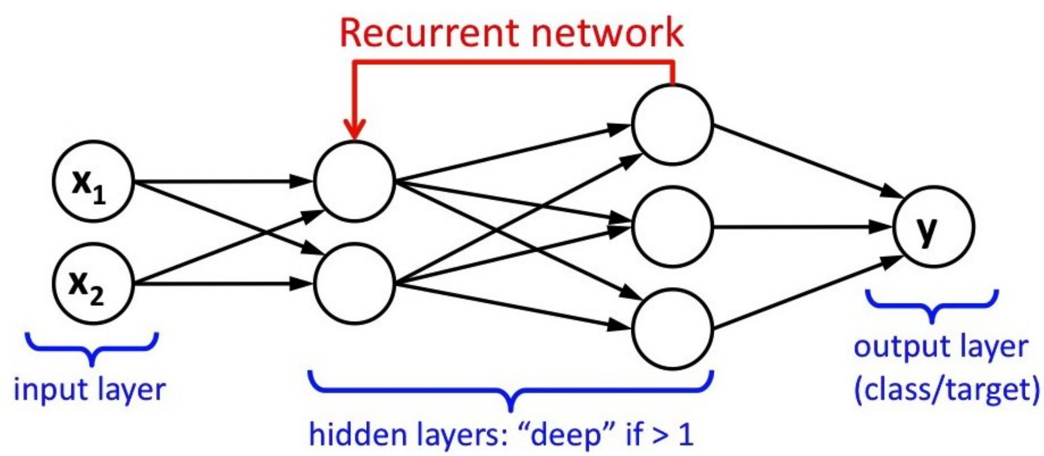
WHAT ARE NEURAL NETWORKS?

- **Forward propagation:** Initially, a randomly selected set of weights are applied throughout the network and an output is calculated.
- **Back propagation:** A margin of error is calculated of the output and the weights are adjusted to decrease the error.
- To get a final value, we apply an activation function to the hidden layers.
- The purpose of the activation function is to transform the input signal into an output signal and is necessary for the neural network to model non-linear patterns [1].



RECURRENT NEURAL NETWORKS

- Recurrent neural networks are a class of neural networks where the connections between neurons form a directed cycle.
- These cycles allow the neural network to update the weights before it reaches the output and propagates back.
- This architecture is called Long Short-Term Memory (LSTM) and it is convenient to classify, process and predict time series data as it updates the weight of time *t* with the information of time *t-1*.

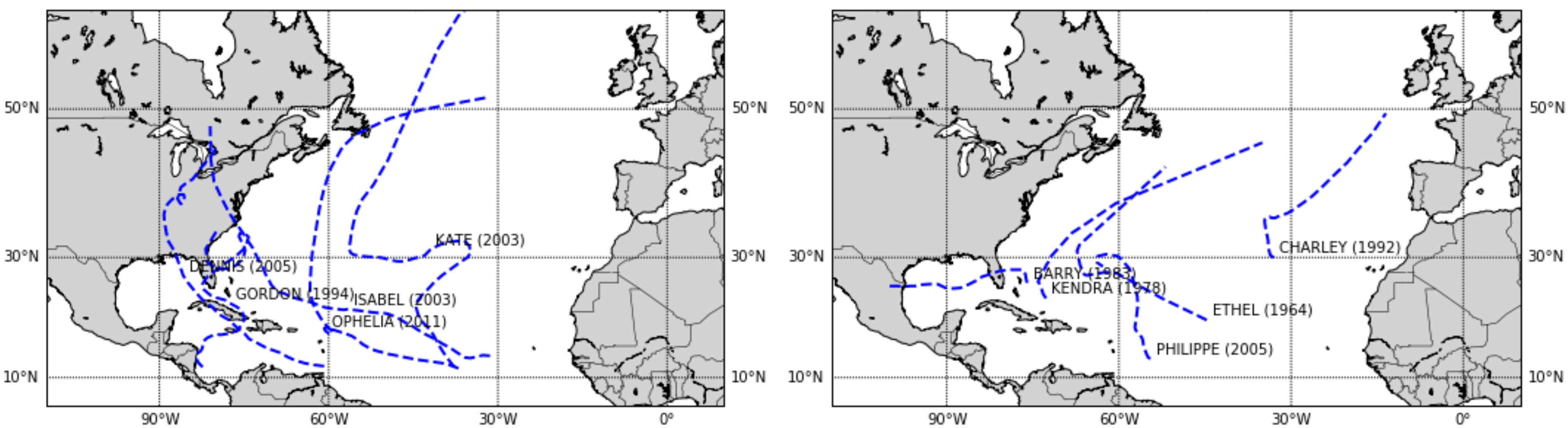


HURRICANES AND NEURAL NETWORKS

- 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.
- 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.

HURRICANE DATA

- The raw Atlantic hurricane/tropical storm data used in this project were extracted from the NOAA database provided at: http://weather.unisys.com/hurricane/atlantic/
- The features provided were latitude and longitude coordinates, wind speed, and pressure.



Hurricane trajectory samples from dataset

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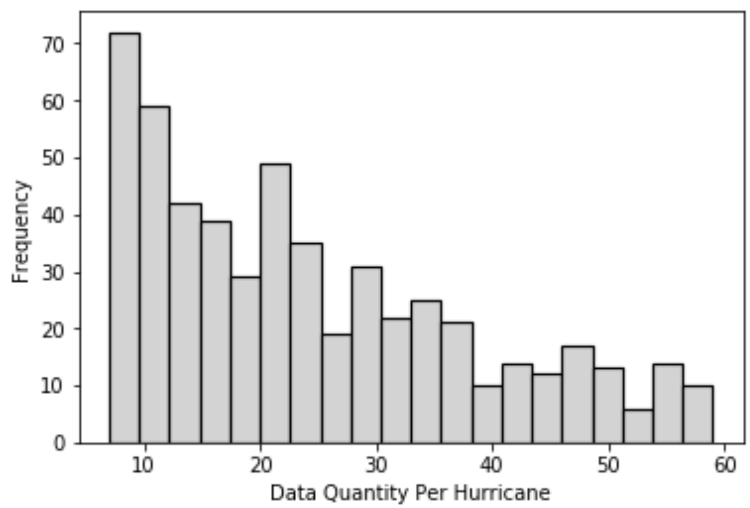
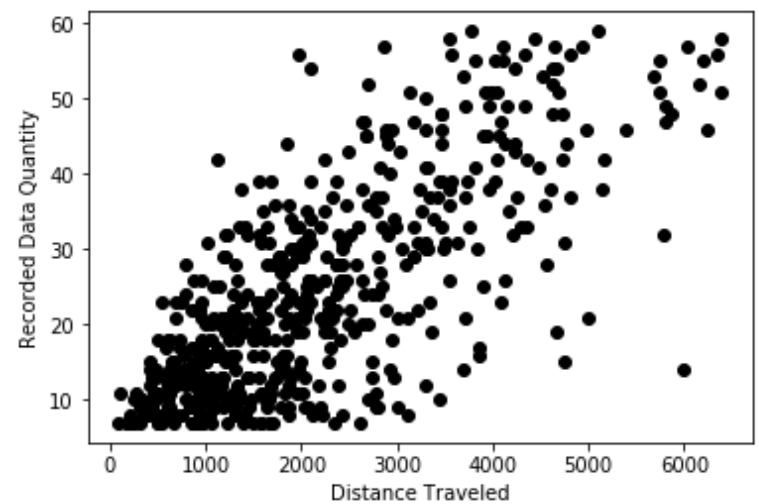
HURRICANE DATA

- Figure 2 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.)
- Figure 3 shows a direct correlation between the number of data points collected per historical track and the total distance traveled.



Data Points Per
Hurricane vs. Frequency



Data Points Per Hurricane vs.
Distance Traveled

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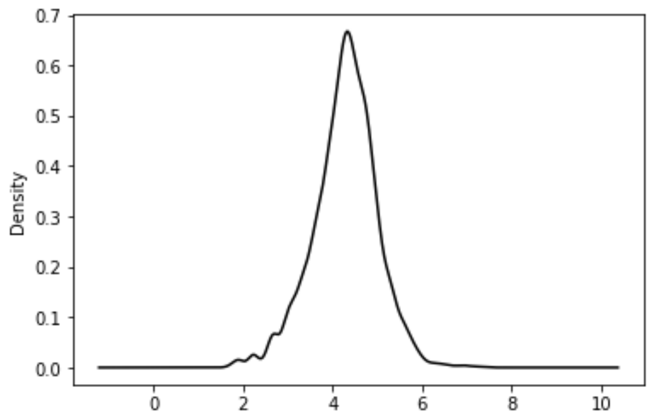
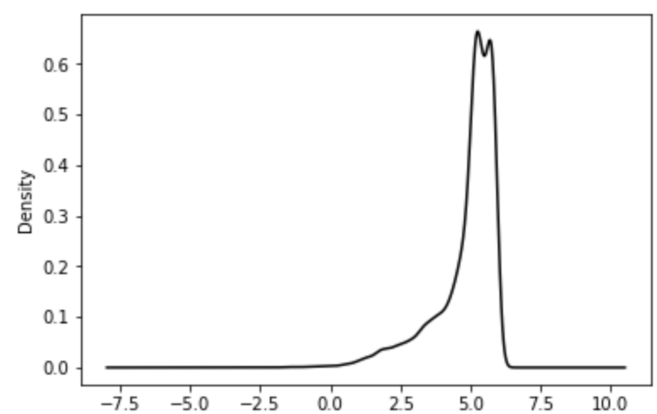
HURRICANE DATA

- Converting from an absolute parameter (latitude and longitude) to a relative parameter (distance and direction) provides a measure of relation and representation learning for unseen hurricane paths.
- It has been shown that RNN with normalized data learns from every input equally, generalizing better, and converging significantly faster [2].



Distance Probability Distribution



Direction (Angle of Travel) Probability Distribution

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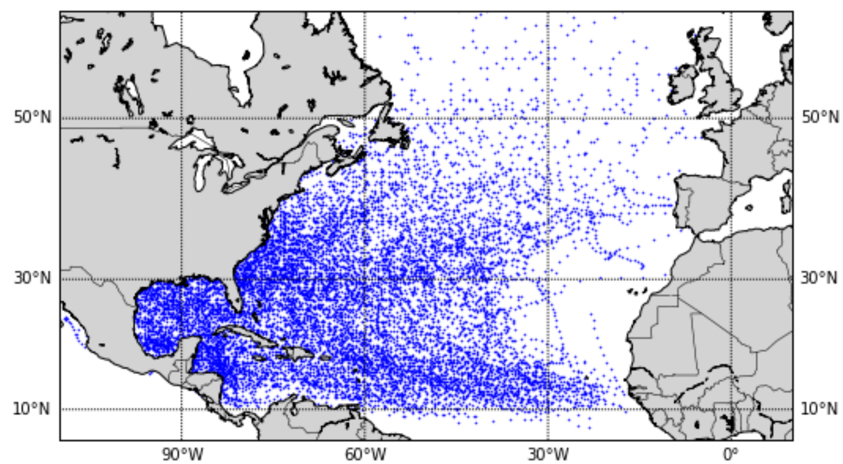
MODEL

- 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.
- 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 allows us to control the amount of loss used by prediction [3].



All plotted latitude and longitude points from dataset

MODEL HYPERPARAMETERS

Grid Boundaries:

- The number of grid blocks in our model could be tuned depending on the amount of hurricane data available.
- 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.

Hidden Layers:

- 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 [4].
- We used 3 hidden layers each with a long short-term memory cell to properly encapsulate the complexity of hurricane trajectory behavior.

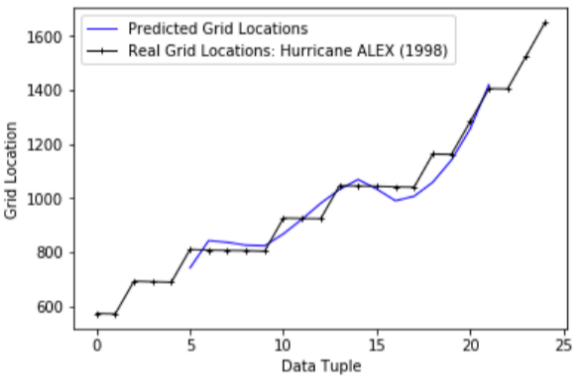
MODEL IMPLEMENTATION

- For the implementation of our model, we utilized Keras. Keras is an application program interface (API) that integrates with lower-level deep learning languages such as TensorFlow.
- Keras 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 NASA [5].
- The learning rate is the rate at which the RNN when updating the weights using Stochastic Gradient Descent at each hidden layer [6].
- The model was trained on an NVIDIA GeForce GTX 1060 with 6GB of RAM which allowed the model to complete training in 200 seconds.

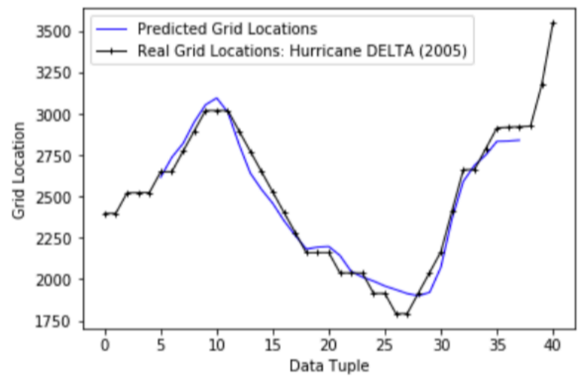
MODEL TRAINING

- 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.
- 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 [7].
- 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.

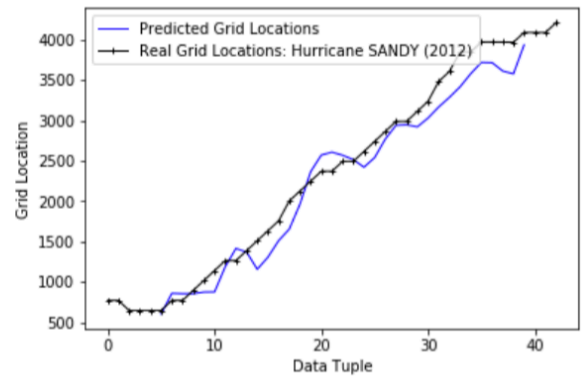
FORECAST RESULTS



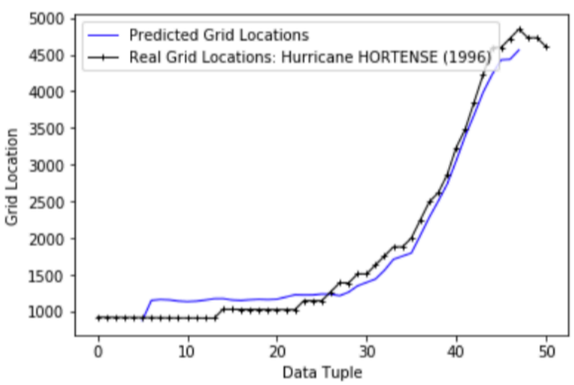
(a) Hurricane ALEX (1998)



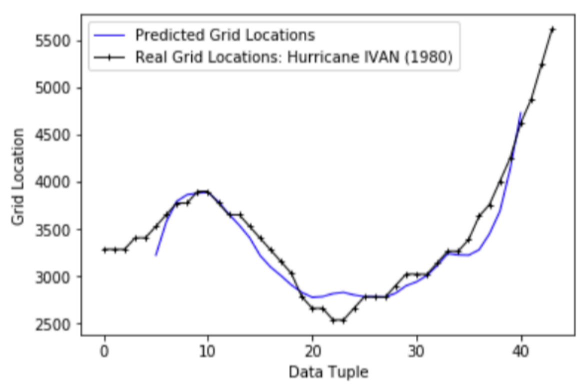
(b) Hurricane DELTA (2005)



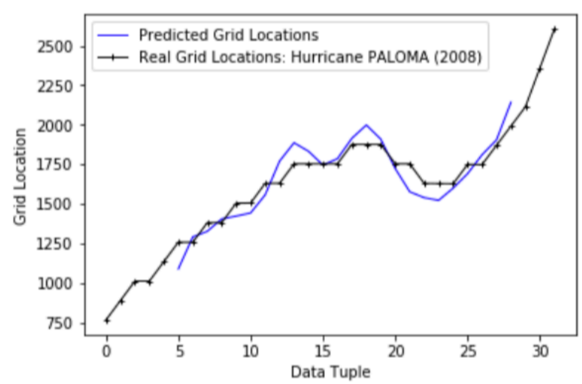
(c) Hurricane SANDY (2012)



(d) Hurricane HORTENSE (1996)



(e) Hurricane IVAN (1960)



(f) Hurricane PALOMA (2008)

6 Randomly Selected Atlantic Hurricane Trajectory Predictions

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FORECAST RESULTS

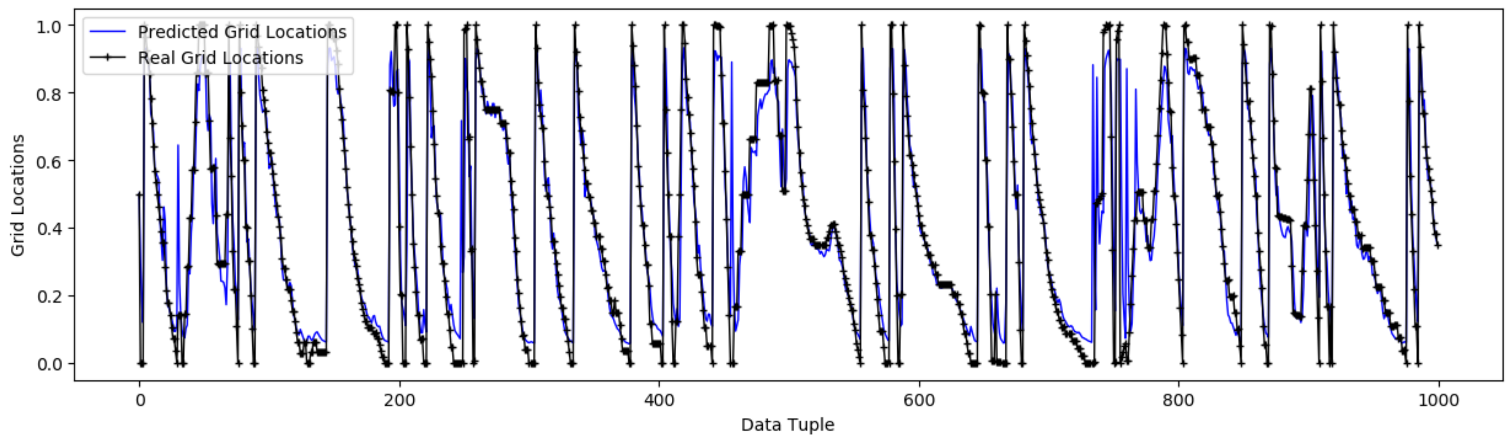
- We compare to another RNN used to predict hurricane trajectories. This method, although presented impressive results, lacks in modeling and forecasting hurricane behaviors that occur frequently in nature. Due to their use of Dynamic Time Warping (DTW), they are unable to train or test on hurricanes that contain loops [8].
- Our grid boundaries are located at a 1x1-degree scale to latitude and longitude.

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**

Our Grid-Based RNN vs. Sparse RNN

CONCLUSIONS

- 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.
- 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.



Hurricane Predictions for All Data Tuples

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FUTURE WORK

- 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

[1] 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.

[2] Tim Cooijmans, Nicolas Balas, Cesar Laurent, Caglar Gulcehre, and Aaron Courville. Recurrent batch normalization. *arXiv preprint arXiv:1603.09025*, 2016.

[3] Gene E Birchfield. Numerical prediction of hurricane movement with the use of a fine grid. *Journal of Meteorology*, 17(4):406–414, 1960.

[4] Andrej Karpathy, Justin Johnson, and Li Fei-Fei. Visualizing and understanding recurrent networks. *arXiv preprint arXiv:1506.02078*, 2015.

[5] Keras API: https://keras.io/layers/recurrent/

[6] Junyoung Chung, Caglar Gulcehre, KyungHyun Cho, and Yoshua Bengio. Empirical evalua- tion of gated recurrent neural networks on sequence modeling. *arXiv preprint arXiv:1412.3555*, 2014.

REFERENCES

[7] Andrada E Ivanescu, Peng Li, Bran- don 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.

[8] Mina Moradi Kordma- halleh, 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.

THANK YOU!