DeepRI: End-to-end Prediction of Tropical Cyclone Rapid Intensification from Climate Data

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1 Background

Tropical cyclones (a.k.a Hurricanes) are among the most destructive natural phenomena in the world. With $15.6 billions average event cost, Tropical cyclone (TC) real-time forecasting and risk mitigation is of great importance. However, though TC track forecasting has improved significantly in the past decades, intensity forecasting still shows large forecast error, largely due to the challenge in predicting TC rapid intensification.

Rapid intensification (RI) is the significant strengthening in storm wind speed within a short time (e.g. >30 kt over 24 hours), and almost all historical category 4 and 5 hurricanes are RI storms (7). To mitigate the potential high damage and risks, predicting rapid intensification has been identified as one of the highest operational forecasting priorities in the National Hurricane Center (NHC). Even though, RI prediction is still challenging as it involves multi-scale physical interactions where both environmental and internal convective processes contribute to the RI occurrence (13; 14; 4).

Despite the low predictability, progress has been made in RI prediction. Existing studies can be categorized into three kinds: 1) *Dynamical models*: Dynamical models make prediction by solving primitive equations, however only high-resolution models show skill in NHC (2; 3). While the advantages of higher spatial resolution are consensus when resolving micro-physical processes within the TC, the simulations require accurate initialization and considerable computing power and time for completion; 2) *Statistical models*: Statistical models do not resolve TC inner core, but perform TC intensity forecasting using regression equations with large-scale environmental parameters (9; 8; 15). Statistical models show skill in providing RI probabilistic guidance, however are constraint by their inherent linearity, considering the highly nonlinear meteorological relationships in TC. 3) *Machine learning models*: Recently, machine learning models have been proposed for RI prediction, including naïve Bayes, logistic regression, support vector machines, random forest (16), and deep learning (11). These models have better capacity and can effectively mine signals from the data. However, both statistical models and machine learning models reply on hand-craft features extracted manually from raw climate data.

2 End-to-end Deep Learning for RI

To the best of our knowledge, there is not yet a deep learning model that takes raw climate data and directly make prediction for RI.Such an end-to-end model allows joint optimization over both the feature extraction and the classification model to pursue better global optima. The major advantage of our method compared to others is to automatically learn discriminative features from raw climate data rather than heuristic hand-crafted features (Fig. 1).

Data Preparation we use data from multiple resources including visible and infrared satellite imagery provided by operational geostationary satellites and passive microwave imagery from polar-orbiting satellites, aiming to capture TC inner-core structure and cloud features. To augment the

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Figure 1: End-to-end Rapid Intensification Prediction. We propose to directly predict RI from raw climate data without intermediate heuristic hand-craft features.

training data scale which is important for deep learning, we also use synthetic data from climate model projections, such as HiFLOR, which is able to simulate Category 4 and 5 TCs (12).

We do not extract any features or indices that were heuristically designed to measure hurricane characteristics. Instead, we directly crop 2D patches, e.g. 16×16 in longitude/latitude degree, which corresponds to approximately 1800×1800 in kilometers that are sufficient to cover all surroundings of a single TC. We then concatenate various 2D raw climate data in the channel dimension, which gives us a 2D feature map in dimension of $16 \times 16 \times N$, where N is the number of raw observation.

We train separate models for RI prediction for different lead-time, i.e. 6h, 12h, 18h, 24h, and create corresponding training data sets respectively. For each lead-time, we split independent TCs into training and test split to prevent potential correlations. Overall, this gives us by estimation roughly 4000 TCs in training set, and each TC provides a series of pairs of feature map and ground truth binary label indicating whether RI happens.

Model Architecture Given the nature of our model, which takes 2D feature maps as input and produces a probability or hard decision for RI, there are many convolutional neural network architectures we could refer to. In terms of the capacity from low to high, AlexNet (10), VGG (5), and ResNet (5) are all good options.

Imbalance Data The deep learning model may suffer from data imbalance, since RI rate is pretty low. As a result, the training data contains much less positive data (i.e. RI happens) compared to the negative ones, and a naive random shuffle would likely to lead the network bias toward the negative. Specifically for RI, we propose to use the following methodology to deal with imbalanced data.

1. **Hard negative mining.** Hard negative mining is a typical technique to handle data imbalance problem. The idea is to find a small set of hard negatives (e.g. those similar with the positives) for training rather than random undersample, such that the training data can still maintain balanced. To achieve this, we apply the boosting idea. We sample equal numbers of positive and negative data in a mini-batch. However while positives are sampled randomly, negatives are sampled according to their failure of predictability in previous training iterations.
2. **Hierarchical Cascaded Model.** The training data would be more balanced if we relax the RI criteria, say reducing the amount of intensity strengthen required. Therefore, we can train one model to first detect if the intensification would increase by 10 kt, and then feed all positive predictions into the next model to judge if they may get further intense. The whole problem can be divided and conquered by two sub-models, and the training data for either one is more balanced. The major concern here is that the failure rate accumulate through the cascade, but we could tune model parameters to pursue high recall for earlier stage and high precision for later stage.

3 Summary

In this work, we propose an end-to-end deep learning model to predict Tropical Cyclone Rapid Intensification which automatically learn features from data. The model could potentially serve as an alternative probabilistic guidance other than RI Index (1) in NHC. It could also be coupled with statistical models (1; 6) to improve TC intensity real-time forecasting.

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