HURRICANE NOWCASTING WITH IRREGULAR TIME STEPS USING NEURAL ODE AND VIDEO PREDICTION

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ABSTRACT

Fast and accurate prediction of extreme climate events is critical especially in the recent globally warming environment. Considering recent advancements in deep neural networks, it is worthwhile to tackle this problem as data-driven spatio-temporal prediction using neural networks. However, a nontrivial challenge in practice lies in irregular time gaps between which climate observation data are collected due to sensor errors and other issues. This paper proposes an approach for spatio-temporal hurricane prediction that can address this issue of irregular time gaps in collected data with a simple but robust end-to-end model based on Neural Ordinary Differential Equation and video prediction model based on Retrospective Cycle GAN.

1 INTRODUCTION

Predicting extreme climate events is a pressing and challenging problem that humanity has faced. To make things worse, global warming is changing a developing mechanism and life cycle of extreme climate events. Recent studies show that hurricanes occur increasingly frequently and grow rapidly due to global warming (Emanuel, 2017; Mousavi et al., 2011; Pielke Jr et al., 2005; Schulthess et al., 2018). Thus, it is becoming important to understand dynamics of extreme climate events for accurate and fast prediction.

Traditionally, we have relied on extensive physics-based simulation to predict extreme climate events. Large-scale physics simulation produces high-resolution data, which enables us to explore future scenarios of extreme climate events. However, it is challenging to apply conventional simulation-based methods at a large scale. Specifically, extreme climate events simulation requires exa-scale computing even in moderate resolution. (Hardiker, 1997; Vetter, 2019) Also, global scale of climate data from simulation makes identification and quantitative assessment of extreme climate events difficult, especially when the events are locally nested in a small region of space and time, such as a hurricane.

Thanks to the dramatic development of deep learning, a climate research community has made significant progress in developing models to solve spatio-temporal nowcasting problem of climate events by applying various neural network models (Shi et al., 2017; 2015; Agrawal et al., 2019; Zhang et al., 2017; Kim et al., 2019a;b). Considering temporal dynamics of climate patterns, most of the existing approaches formulate climate nowcasting as a video prediction problem and applied recurrent neural networks (RNNs) to predict the next timestep based on previous timesteps (Shi et al., 2017; 2015; Kim et al., 2019b;a).

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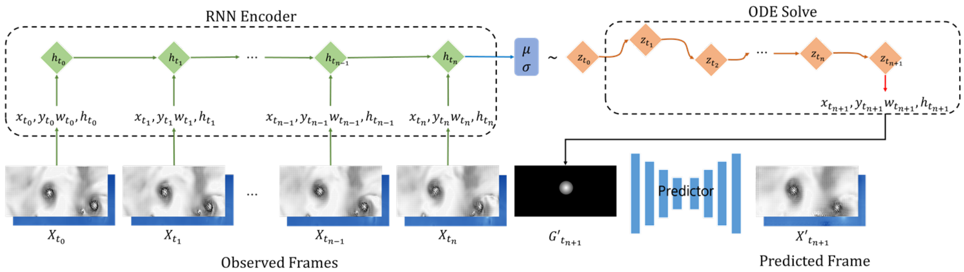

Figure 1: Overview of our proposed model.

RNN-based models, however, have serious drawback on climate event nowcasting, as they inherently assume regular time steps between adjacent time steps. Although this is a reasonable assumption for some other domain such as text, it does not often hold with climate data. First of all, climate data are measured intermittently (e.g., for hours), but we often want to predict in finer temporal resolution for nowcasting. Also, observations are missing frequently. Thus, it is nontrivial to apply vanilla RNN models to this problem. Also, longer-term prediction is extremely challenging with a naive RNN-based model, as the quality of prediction in test-time is gradually degraded along the prediction time. To address these challenges in physics-based and RNN-based methods, we propose a Neural-ODE-based hurricane nowcasting model, that is (1) computationally more efficient, and that can (2) handle input and output with irregular time steps.

Neural ODE (Ordinary Differential Equations) (Chen et al., 2018) is a recently proposed model that can learn representation of an irregularly sampled sequence data. Specifically, it parameterizes the derivative of the hidden state using a neural network instead of specifying a discrete sequence of hidden layers. The output of the network is computed using a differential equation solver. To elaborate the capability of Neural ODE to learn and predict data with irregular time steps, our proposed model combines Neural ODE with a video prediction model in end-to-end manner.

The contribution of proposed model mainly lies in the unified framework for tackling extreme climate nowcasting problem with irregular time steps using Neural ODE and video prediction technique which can be trained end-to-end, with the details listed below:

- **Continuous timestep prediction:** Guided by motional information of hurricane at an arbitrary time point in the future predicted by Neural-ODE, our proposed model can deal with climate data with irregular time step. Specifically, our model can predict future frame after arbitrary timestep given input with irregular timestep.
- **Computationally efficient:** In trade-off between computational cost and accuracy, our model suggest computationally efficient alternative of physics-based climate simulation which can predict near-future hurricane scenario with reasonable accuracy and resolution.

2 Problem Setting and Dataset

Problem Setting. We treat hurricane nowcasting as a video prediction problem. Given a sequence of input hurricane images containing one hurricane trajectory $\mathbf{X} = \{X_{t_0}, X_{t_1}, ..., X_{t_n}\}$, where each image $X_i \in R^{m \times n \times c}$ is an $m \times n$ 2-D climate image with c climate variables (e.g., wind velocity, precipitation, pressure etc), we predict an image at next timestep $X_{t_{n+1}}$. Time steps $\{t_0, .., t_{n+1}\}$ may be irregularly sampled (that is, $t_k - t_{k-1}$ is not necessarily equal for different k).

Dataset. We plan to use 20-year hurricane records from 1996 to 2015 of the *Community Atmospheric Model v5 (CAM5)* dataset Wang & Liu (2014). It contains snapshots of the global atmospheric states every 3 hours with around $0.25°$ ($27.75\ km$) resolution ($1° \approx 111\ km$). Each snapshot is comprised of multiple physical variables, among which we will use zonal wind (U850), meridional wind (V850), surface-level pressure (PSL), given their relevance to hurricane identification from scientific studies. For collecting hurricane labels in CAM5 data, we will use the Toolkit for Extreme Climate Analysis (TECA) (Prabhat et al., 2015; Rübel et al., 2012). TECA is an expert-engineered system with a collection of climate analysis algorithms for extreme event detection, tracking, and other event pattern characterization. The corresponding TECA labels contain spatial coordinate (latitude, longitude) of each hurricane and the diameter of hurricane-force winds. In order to fit the model

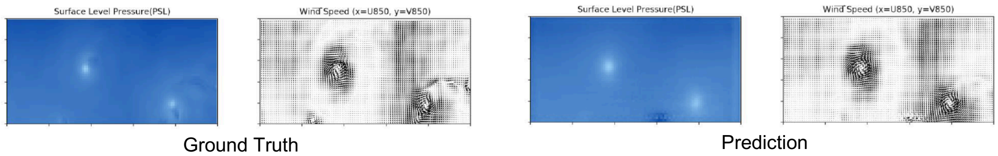

Figure 2: Preliminary results from Retrospective Cycle GAN to predict hurricane in next timestep.

into memory, we will split the global map into several non-overlapping tropical cyclone basins of $60^\circ \times 160^\circ$ sub-images, and only use the period including hurricanes.

3 Proposed Method

We propose a Neural ODE model that learns a hurricane trajectory from irregularly sampled past time steps and predicts a future frame based on it. Our proposed approach is divided into two parts. First, in **Trajectory Prediction** step, the future coordinate of hurricane center is predicted given its previous trajectory at irregular time steps using Neural ODE (Chen et al., 2018). Then, in **Video Prediction** step, we predict actual hurricane video at the future time frame given past images and predicted coordinate values encoded as a Gaussian heat-map.

Trajectory prediction. First, we extract the hurricane's center coordinate (x, y) and magnitude (w, h) from the input hurricane images using TECA. Then, we put them as the input to Neural ODE together with arbitrary time interval we want to predict, $t_{n+1} - t_n$, and predict $(x_{t_{n+1}}, y_{t_{n+1}}, w_{t_{n+1}}, h_{t_{n+1}})$ of the hurricane at next timestep t_{n+1}. The interval between each time step, $\{t_2 - t_1, ..., t_{n+1} - t_n\}$ can be irregular.

To effectively conditioning the hurricane coordinates predicted by trajectory predictor at video prediction step, we generate an image (same size with the hurricane image) containing a Gaussian heat-map from the predicted coordinate. To make this Gaussian heat-mapping step differentiable, we adopt Jakab et al. (2018) so that trajectory and video prediction are trained jointly. A Gaussian heat-map $G'_{t_{n+1}}$ is encoded using estimated coordinates and magnitude. The Gaussian heat-map $G'_{t_{n+1}}$ which contains structural information of hurricane at t_{n+1} is utilized as a conditioning information to predict the next frame, X'_{n+1}, in video prediction stage.

Video prediction. As shown in Figure 1, the encoded heat-map $G'_{t_{n+1}}$ is given together with previous frames, $\{X_{t_0}, ..., X_{t_n}\}$, to the video prediction model to predict the next frame X'_{n+1}. For the video prediction, we propose to adopt Retrospective Cycle GAN (Kwon & Park, 2019) which shows state-of-the-art performance. This model is trained bi-directionally; that is, predicts a future frame from past ones as well as predicts a past frame from reversed input frames by putting the predicted future frame as input. In this way, the future frame is predicted as adapting to the entire dynamics of the video. We chose Retrospective Cycle GAN as it is especially suitable to model motional dynamics of a hurricane over time both in forward and reverse direction. We convert the model into conditional input setting, in which takes previous video frames $\{X_{t_1}, ..., X_{t_n}\}$ and Gaussian heat-map $G'_{t_{n+1}}$ to predict $X'_{t_{n+1}}$. Simultaneously, the reversed input sequence $\{X_{t_{n+1}}, ..., X_{t_2}\}$ and Gaussian heat-map G'_{t_1} is fed to make a prediction of X'_{t_1}. At the inference time, the model outputs a future frame with given preceding video frames.

Preliminary Experiment. Figure 2 shows our preliminary results from a toy experiment to predict next time frame hurricane image based on 5 previous time steps. It shows that Retrospective Cycle GAN can predict hurricane with reasonable quality.

4 Applications and Social Impact

Ultimate goal of this work is applying our model to sparsely measured climate observation data. The capability of proposed model to learn complicate dynamics of hurricane even from irregularly sampled data and to predict future in arbitrary time step with relatively economic computation cost than physics-based simulation will support and expedite risk-management and disaster prevention plan from extreme climate events. The output of our model can also be a good resource for climate scientists in the process of parameterization for the numerical weather prediction model.

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