Hurricane Detection in Climate Simulation Data with ConvLSTM

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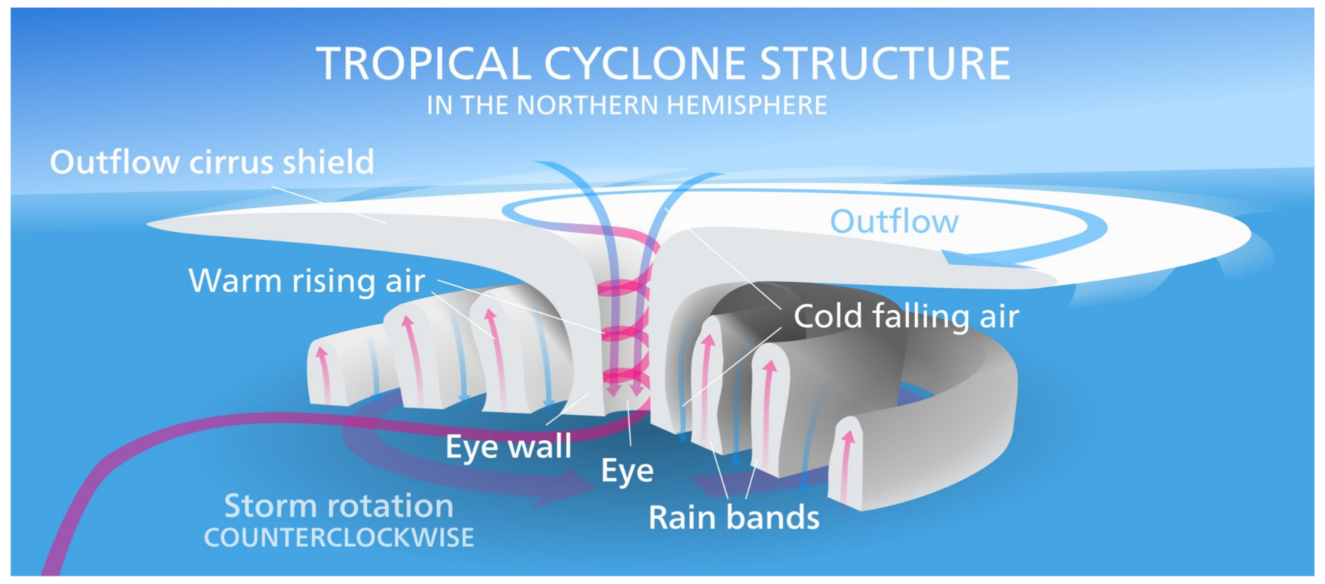
Introduction

- The detection of extreme climate events in climate simulation data can be computation heavy using the traditional algorithms.
- Here we propose a machine learning method using ConvLSTM network which takes less time after the model is trained.
- Hurricane are produced with a low pressure center and a spiral arrangement of strong winds and heavy rainfall.



Data

- 20 years data from 1996 to 2015 of Community Atmospheric Model v5 (CAM5) dataset [1]
- It contains 3-hourly records of global atmospheric states which comprised of multiple physical variables.
- Region around the Northern hemisphere which is 180° to 340° longitude and 0° to 60° latitude with 0.5° (55.5 km) resolution.
- Ground Truth: binary density map created from hurricane's location and diameter generated by the Toolkit for Extreme Climate Analysis (TECA) [3]

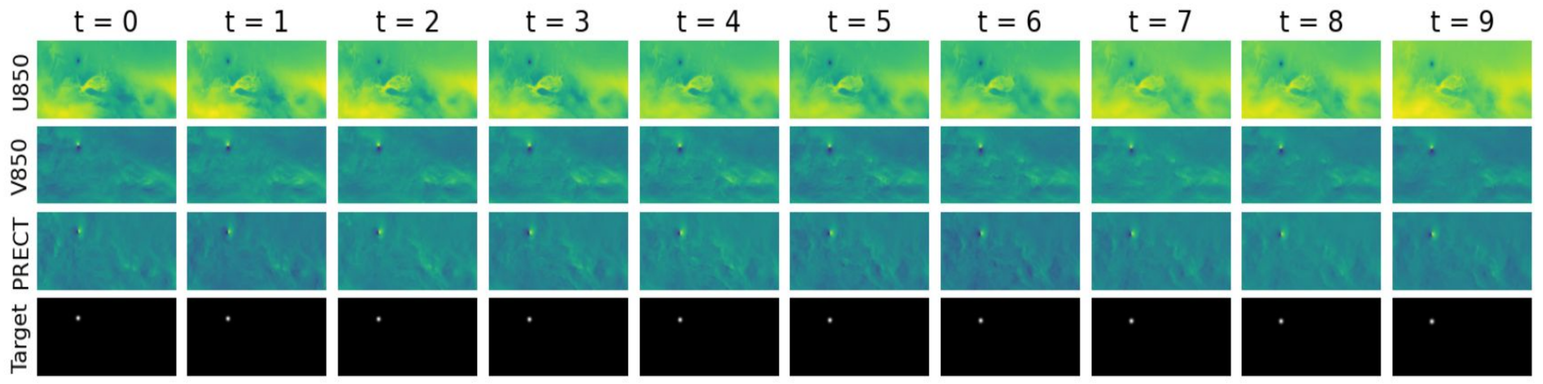


Figure 1. Input data with truth labels for a single data sample which is a subsequence of length 10.

Convolutional LSTM

- FC-LSTM (Fully Connected Long Short-Term Memory Network)
- Encodes temporal information

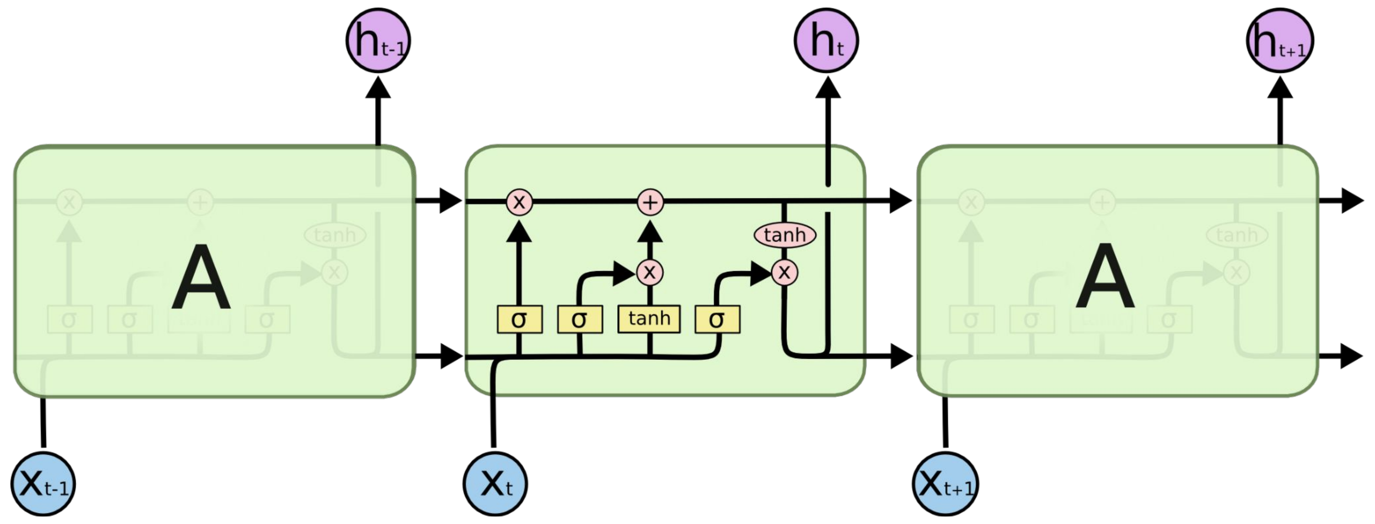


Figure 2. The inner structure of several connected FC- LSTM cells. Image credit from [4]

- ConvLSTM (Convolutional LSTM) [2]
- Replace fully connected layers of LSTM with convolution operation
- Encodes both spatial and temporal information
- Has less redundancy than fully connected layers

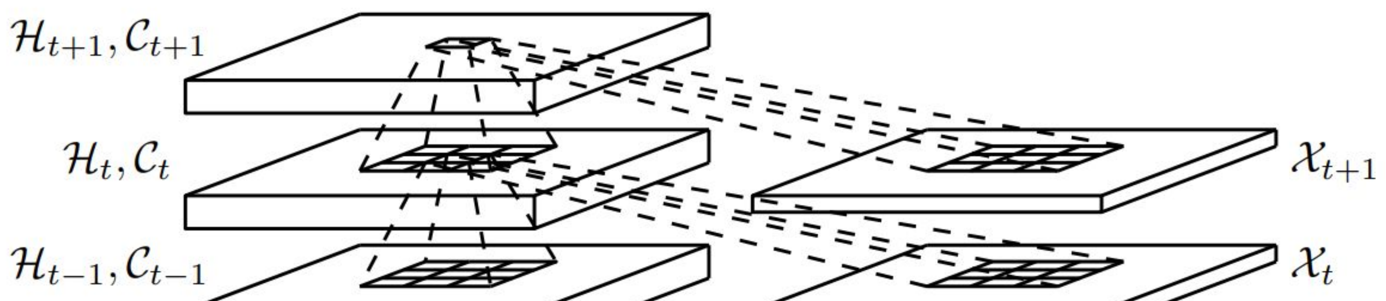


Figure 3. Inner structure of Convolutional LSTM network [2]

- Each pixel is updated by considering neighbor pixels in a set region of previous state by convolution operation
- With more levels, each output pixel is affected by a wider range from the input image

- A regression task where we are trying to minimize the pixel-wise min squared loss between predicted and ground truth density maps.

Experiment Settings

- Model is comprised of 3 layers of ConvLSTM network [1]
- 3408 train samples
- 672 test samples
- Each data sample is a subsequence of length 10 (30 hours)
- Three variables are used: PRECT (precipitation), U850 (zonal wind at 850 hPa pressure level), V850 (meridional wind)

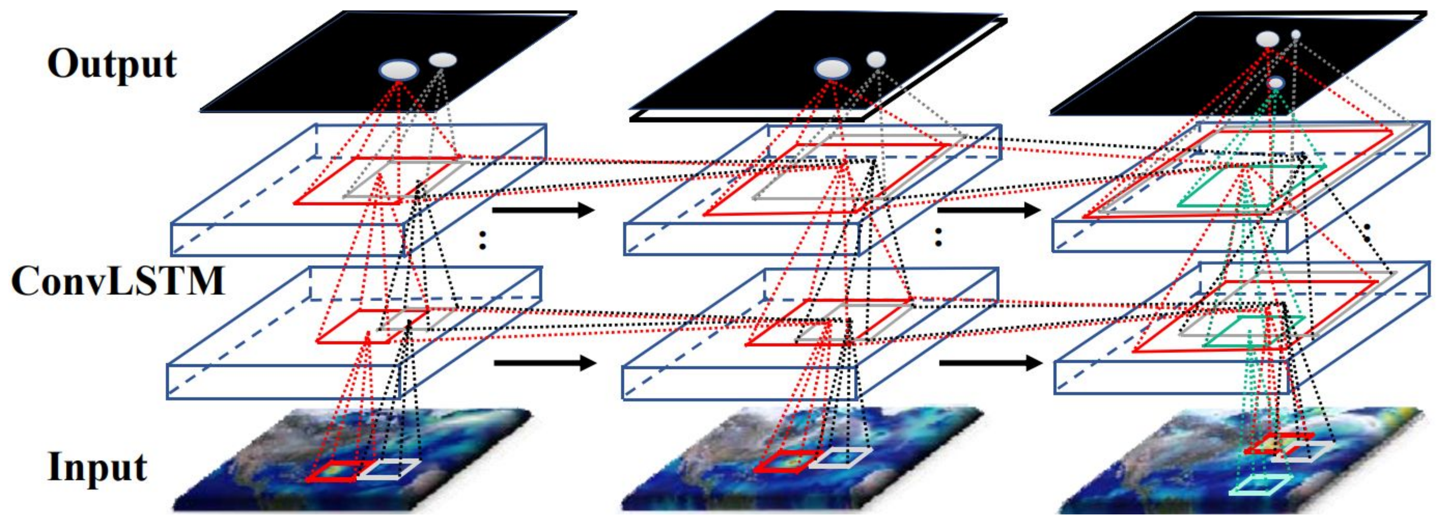


Figure 4. Structure of a 2-layer ConvLSTM model. Image credit from [1]

Evaluation

- Intersection Over Union (IOU)
- Mean squared loss
- Dice coefficient

Future Work

- Use more physical variables related to hurricane formation for data
- Use more accurate image segmentation for ground truth.

References

[1] S. Kim et al., "Deep-Hurricane-Tracker: Tracking and Forecasting Extreme Climate Events," 2019 IEEE Winter Conference on Applications of Computer Vision (WACV), Waikoloa, HI, USA, 2019, pp. 1761-1769, doi: 10.1109/WACV.2019.00192.

[2] X. Shi, Z. Chen, H. Wang, D.-Y. Yeung, W.-K. Wong, and W.-c. Woo. "Convolutional LSTM network: A machine learning approach for precipitation nowcasting." In *Advances in Neural Information Processing Systems (NIPS)*, 2015.

[3] O. Rubel, S. Byna, K. Wu, F. Li, M. Wehner, W. Bethel, et al. "TECA: A parallel toolkit for extreme climate analysis." *Procedia Computer Science*, 9:866–876, 2012.

[4] https://colah.github.io/posts/2015-08-Understanding-LSTMs/