Hurricane Nowcasting with Irregular Time-step using Neural-ODE and Video Prediction

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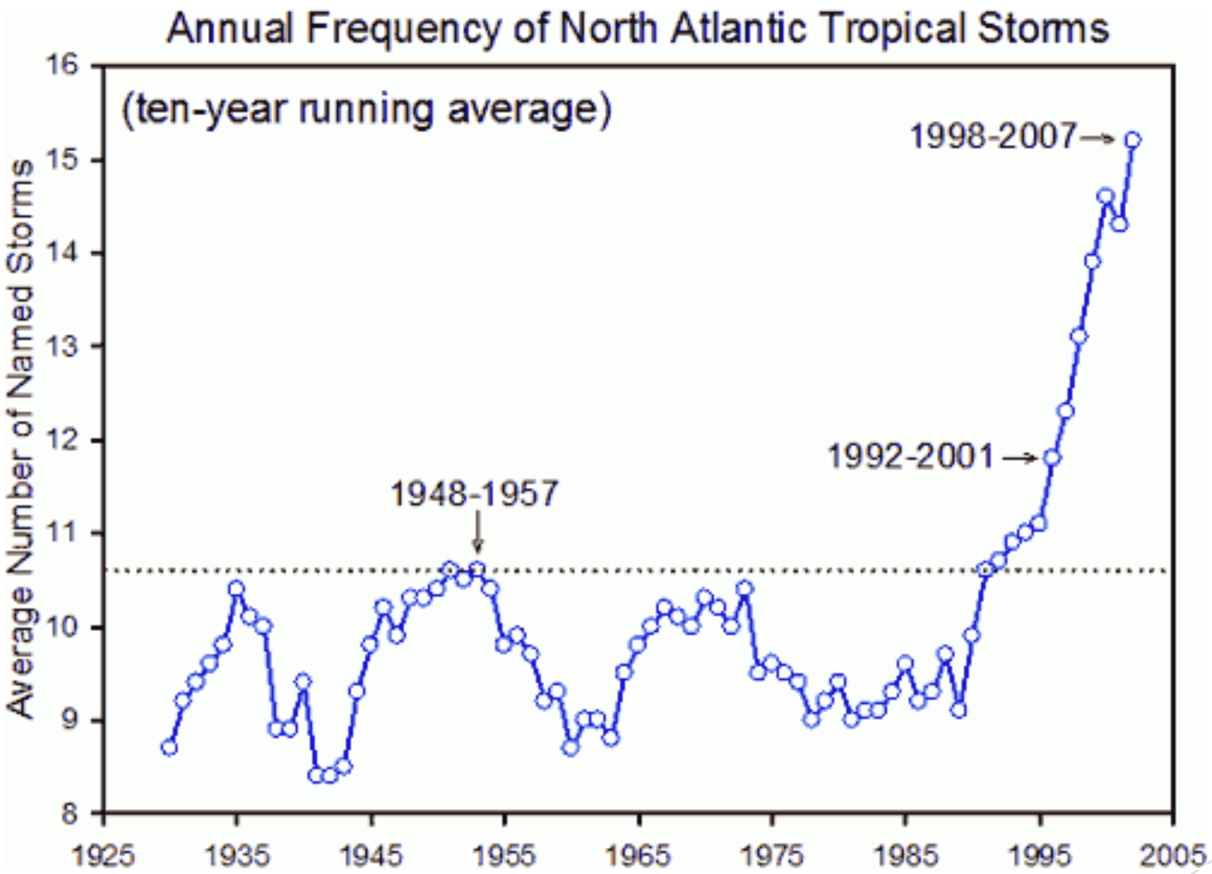
Motivation

1. Global Warming and Extreme Climate Events

- Hurricane: **More frequent, Grow more rapid**

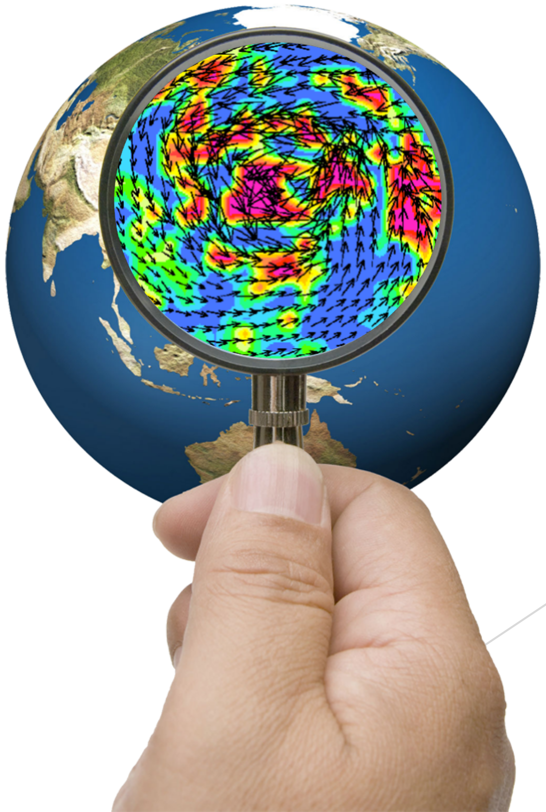


Pew Centre, "Globally, there is an average of about 90 tropical storms a year". The IPCC AR4 report (2007)

Motivation

2. Conventional Numerical Prediction Method
   (Large scale physics simulation for high resolution climate nowcasting)

- **Expensive:** Exa-scale computing
- **Locally nested event, domain knowledge**
  - Labor intensive
  - Expert based



Neural net-based Climate Nowcasting model

1. Regional prediction on local area:
   - Cheap but reasonably accurate
2. Mostly RNN-based Model:
   - ConvLSTM, ConvGRU, Vanilla RNN etc
   - Problem: Assume only regular time-steps btw adjacent time-step
     1. Missing Observation data: Irregular time-step
     2. Cannot predict finer temporal resolution than measured interval
     3. Challenging to predict longer-term:
        Quality is degraded along the prediction time

Neural ODE based hurricane nowcasting:
1. Computationally efficient
2. Irregular/Continuous time-step

Neural-ODE

1. **ODE Solver**

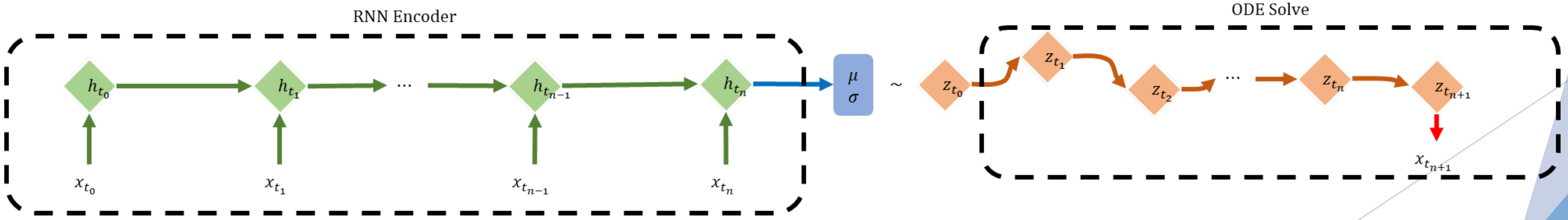
$$z(t_1) = z(t_0) + \int_{t_0}^{t_1} f(z(t), t, \theta)dt = ODESolve(z(t_0), \overset{\text{time step}}{\boxed{t_0, t_1}}, \underset{\text{nn parameter}}{\boxed{\theta, f}})$$

2. **Latent-ODE**
   - Continuous time-step prediction
   - Learn representation of an irregularly sampled sequence data

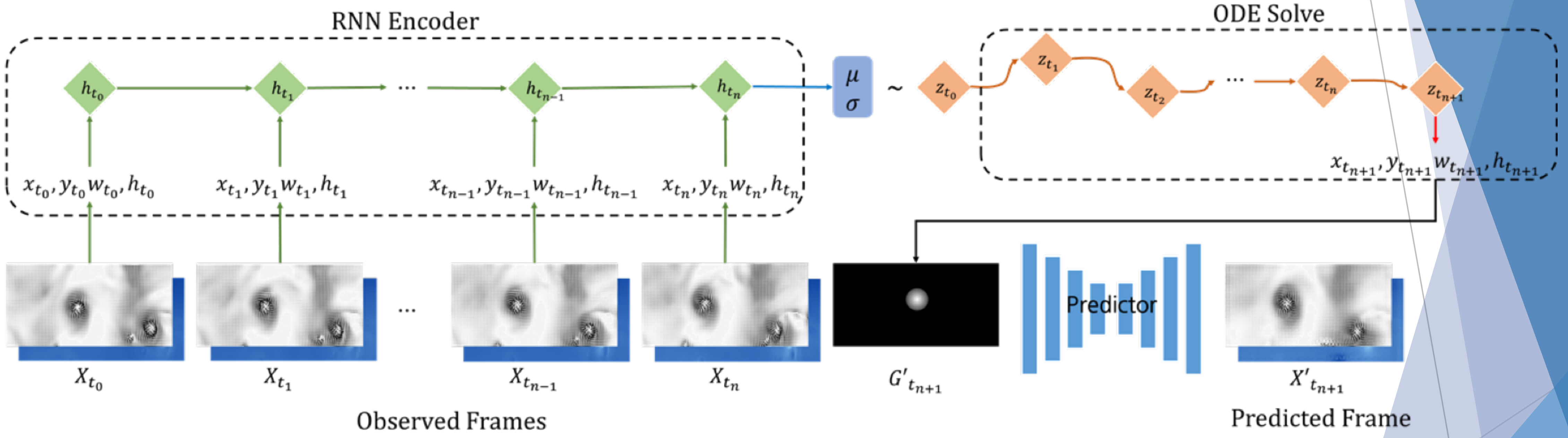
$$q(\mathbf{z}_{t_0} | \{\mathbf{x}_{t_i}, t_i\}_i, \phi) = \mathcal{N}(\mathbf{z}_{t_0} | \mu_{\mathbf{z}_{t_0}}, \sigma_{\mathbf{z}_0})$$

$$\mathbf{z}_{t_0} \sim q(\mathbf{z}_{t_0} | \{\mathbf{x}_{t_i}, t_i\}_i)$$

$$\text{ELBO} = \sum_{i=1}^{M} \log p(\mathbf{x}_{t_i} | \mathbf{z}_{t_i}, \theta_{\mathbf{x}}) + \log p(\mathbf{z}_{t_0}) - \log q(\mathbf{z}_{t_0} | \{\mathbf{x}_{t_i}, t_i\}_i, \phi), \text{where } p(\mathbf{z}_{t_0}) = \mathcal{N}(0, 1)$$



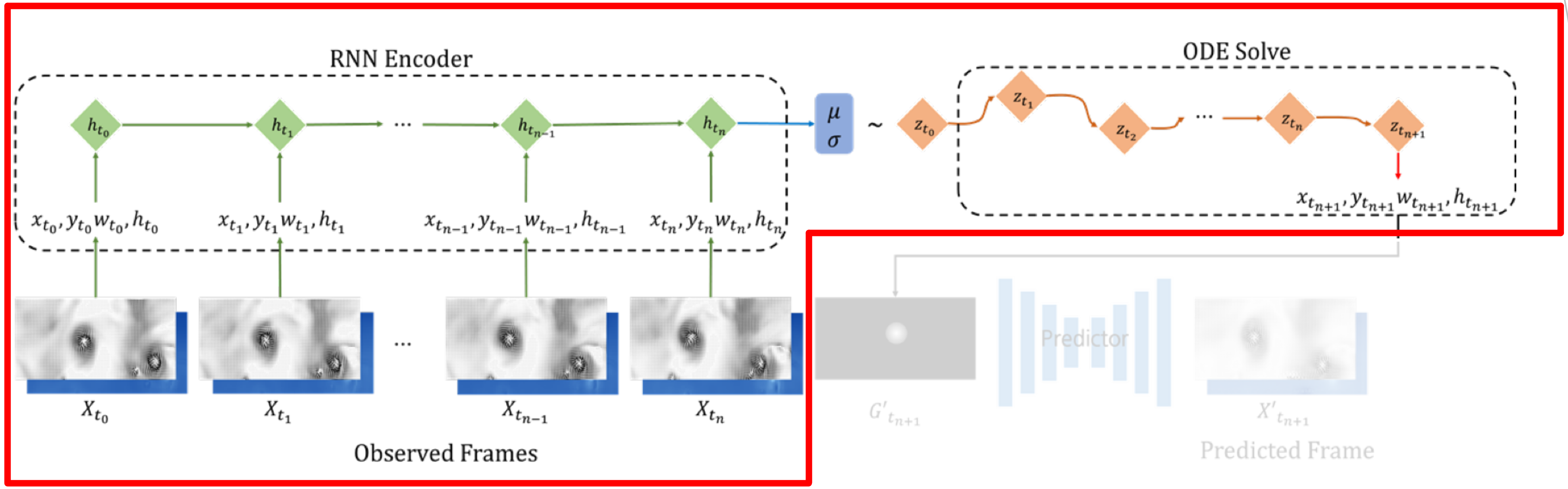
Framework of our model:
Overview



- **Goal:** Hurricane Nowcasting from irregularly sampled spatio-temporal climate data

1. **Trajectory Prediction:**
   Irregular time-step hurricane center prediction using Neural ODE
2. **Video Prediction:**
   Predict hurricane Video at future time frame, given (1) predicted center and (2) past images using R-Cycle GAN

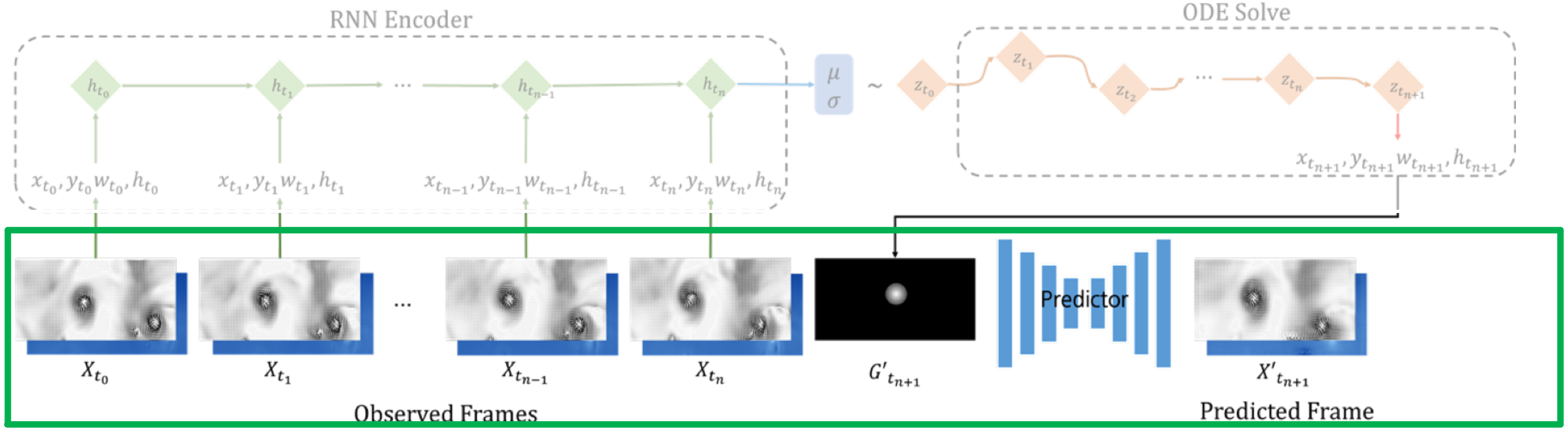
Framework of our model:
Trajectory Prediction using **Neural ODE**



1. Extract bounding box information, $bb_i = \{x_i, y_i, w_i, h_i\}$, from Irregularly sampled spatio-temporal climate data containing hurricane: $X_{t0},\dots,X_{tn}$
2. Neural ODE predict bounding box information at next time step: $bb_{tn+1}=\{x_{tn+1}, y_{tn+1}, w_{tn+1}, h_{tn+1}\}$
   Interval between each time step is irregular: $\triangle t = \{t_{n+1}-t_n\}$
   $$bb_{tn+\triangle t} = \text{Neural ODE}(\triangle t, bb_0, \dots, bb_{tn})$$

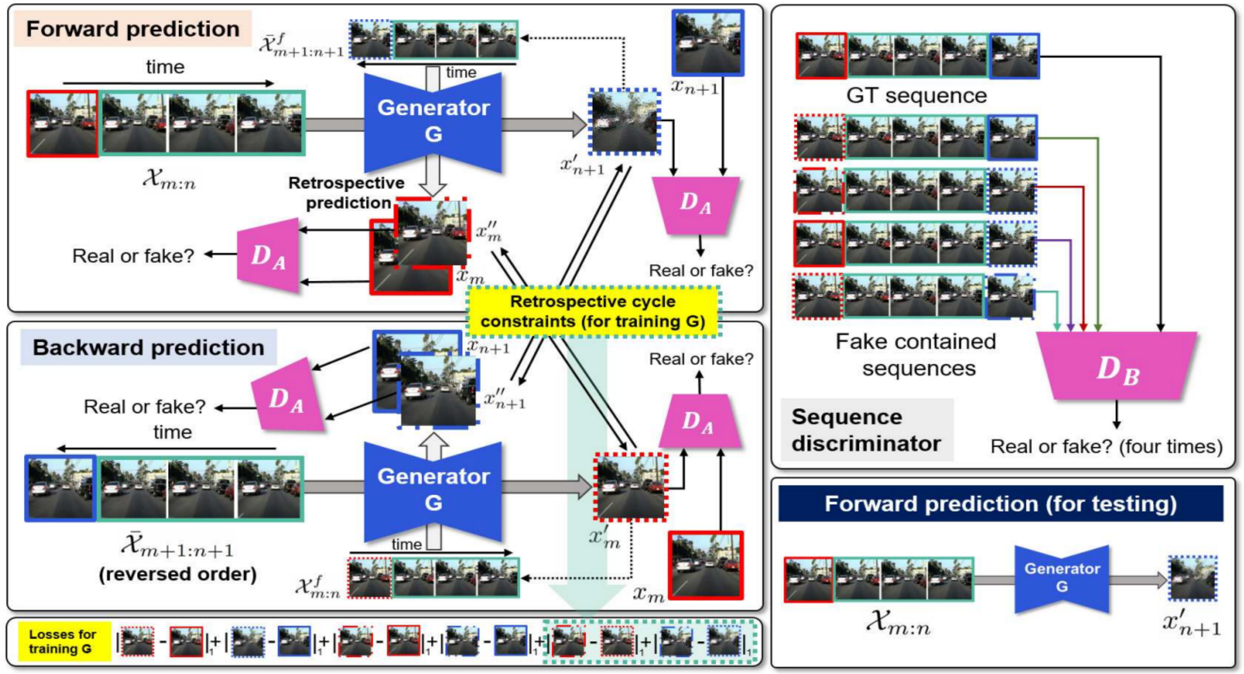
Rübel, Oliver, et al. "Teca: A parallel toolkit for extreme climate analysis." Procedia Computer Science 9 (2012): 866-876.

Framework of our model:
Video Prediction using **R-Cycle GAN**



1. Encode predicted bounding box information as Gaussian heat-map
   : $\{x_{tn+1}, y_{tn+1}, w_{tn+1}, h_{tn+1}\} \rightarrow G'_{tn+1}$
2. Predict Next time frame using Video Prediction Model (f), conditioning heat-map and previous frames.
   : $X'_{tn+1} = f(X_{tn+1} \mid G'_{tn+1}, X_{t0}, \ldots, X_{tn})$
3. Use R-Cycle GAN as Video Prediction Model, f

Framework of our model:
Retrospective Cycle GAN (R-Cycle GAN)



- Suitable to model motional dynamics of a hurricane over time by considering both in forward and reverse direction
- Convert R-cycle GAN in conditional input setting

1. **Forward:** takes previous video frames {X_{t1} , …, X_{tn} } and Gaussian heat-map, G'_{tn+1} to predict X'_{tn+1} .
2. **Reverse: take reversed** input sequence {X_{tn+1} , …, X_{t2} } and Gaussian heat-map G'_{t1} is fed to make a prediction of X'_{t1} .
3. **Inference time:** the model outputs a future frame with given preceding video frames.

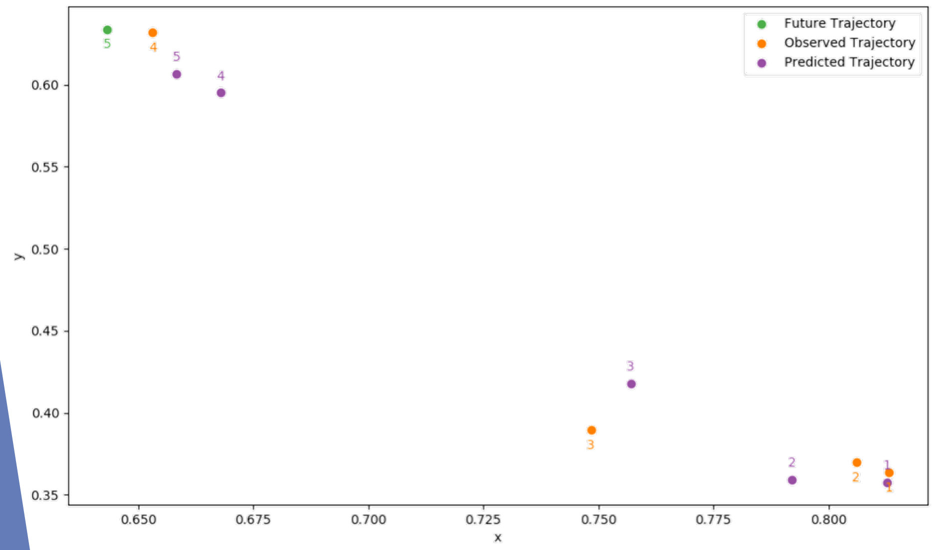
Dataset

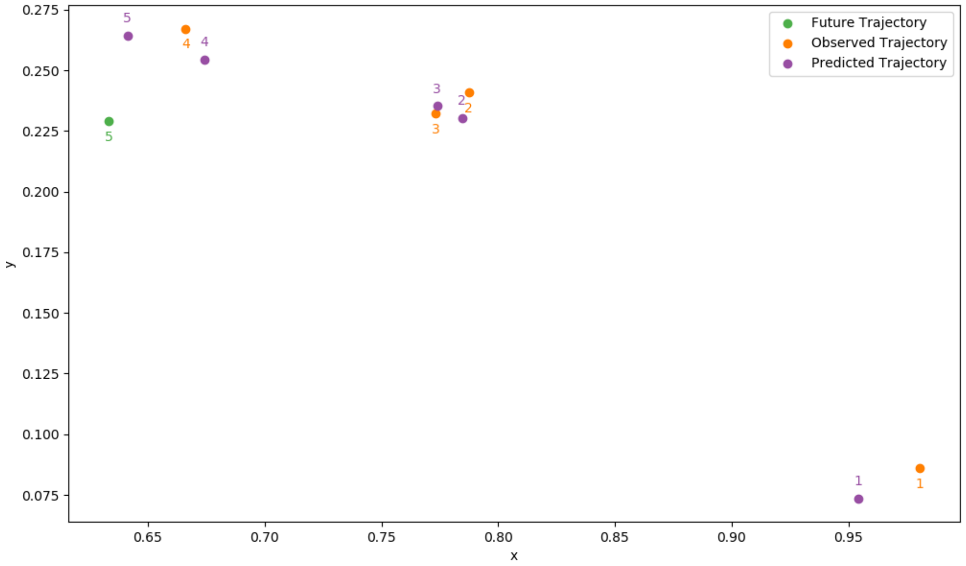
- Community Atmospheric Model v5 (CAM5) dataset:
  - 20 years hurricane records from 1996 to 2015
  - Resolution: 0.25^{o} (27.75 km)
  - Climate variable Channels: Among 16 channels picked 4
    zonal wind (U850), meriodional wind (V850), surface-level pressure (PSL)
- Labeling:
  - TECA (Toolkit for Extreme Climate Analysis):
    An expert engineered system to analyze extreme climate events
  - Label: spatial coordinate of hurricane center (latitude, longitude), diameter of hurricane-force wind
- Regional Input:
  - Divide Global map as non-overlapping TC basins of 60^{o} x160^{o} sub-image
  - Collect period including hurricanes

Rübel, Oliver, et al. "Teca: A parallel toolkit for extreme climate analysis.” Procedia Computer Science 9 (2012): 866-876.

Preliminary Results (Neural ODE)

- Hurricane Trajectory Prediction
  - Use only hurricane center's coordinate (x_t, y_t)
  - Predict hurricane center (x_{t_5}, y_{t_5}) with observed trajectory $\{(x_{t_1}, y_{t_1}), (x_{t_2}, y_{t_2}), (x_{t_3}, y_{t_3}), (x_{t_4}, y_{t_4})\}$
  - Interval btw each time-step, $\{t_2 - t_1, \ldots, t_5 - t_4\}$ is irregular

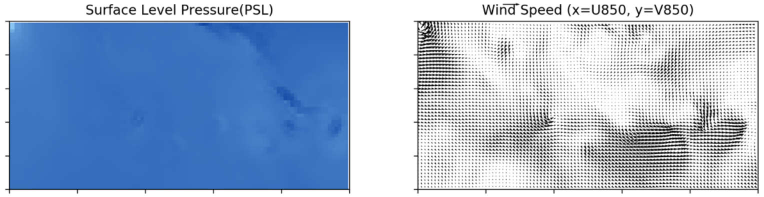




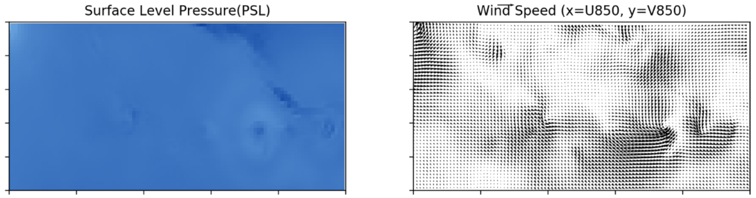
Preliminary Results (R-Cycle GAN)

Time steps **Video frame inputs**

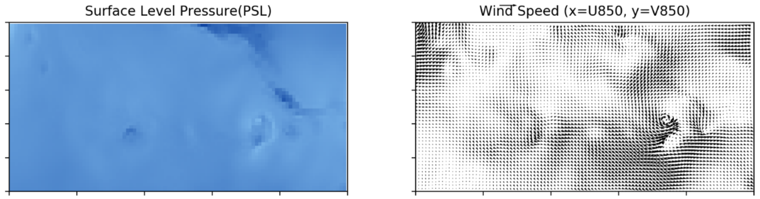
t=1



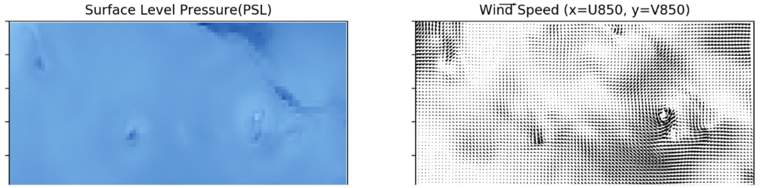
t=2

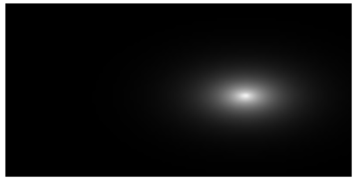


t=3



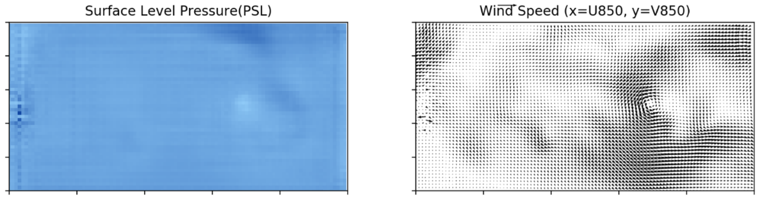
t=4



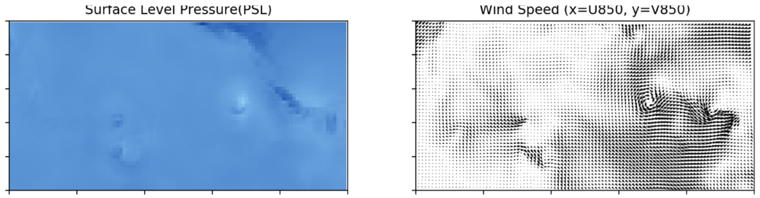


Condition for predicting t=5

Predicted t=5



GT t=5



Contributions and Social Impacts

- Contributions

1. Proposed model learns dynamics of hurricane even from irregularly sampled data
2. Proposed model predict future in arbitrary time step (predict finer timestep or long future)
3. Low computational cost

- Applications and Social Impacts

1. Predict future from sparsely measured climate observation data.
2. Expedite Risk-management and disaster prevention plan

Question and Discussion

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