Online LSTM Framework for Hurricane Trajectory Prediction

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Outline

- Introduction
- Proposed Framework
- Experiments
- Conclusion

Background

- Hurricanes can cause severe damages when strike land
  - Hurricane Dorian (2019) causes more than $5.1 billion damages and 84 confirmed death

- Accurate long-range forecasting of the hurricane tracks is essential to save lives and property loss

Previous Works

- Previous works
  - Uses either historical data, meteorological data, or outputs from physical models
  - Mostly batch learning only
    - Not suitable for non-stationary data

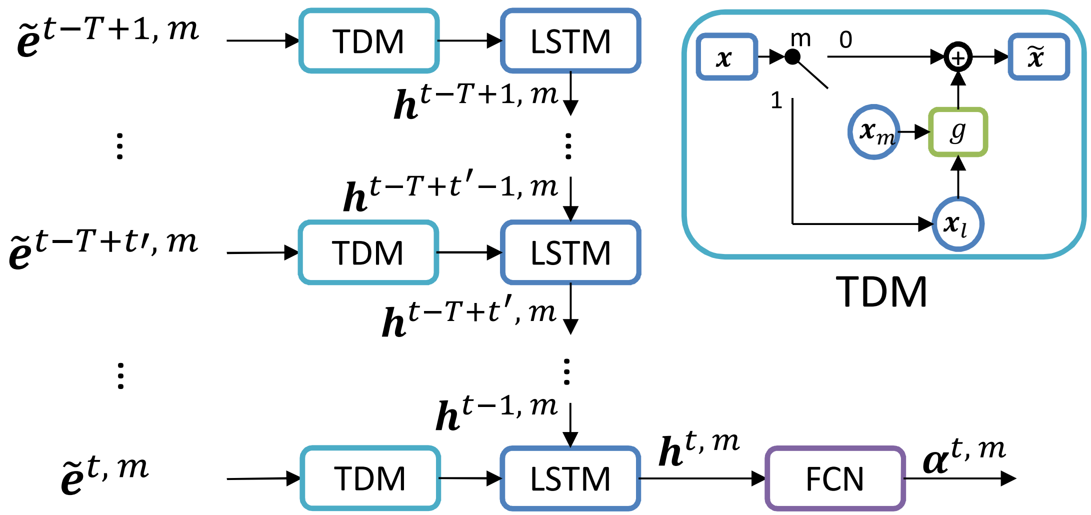
Reference	Method	Input Features	Prediction Task	Lead Time (Forecast horizon)	Learning Mode
Moradi Kordmahalleh et al. 2016	RNN	Historical data	Trajectory	Multi-step (12 hrs)	Batch
Cox et al. 2018	Association rule	Historical data	Trajectory	Multi-step	Batch
Mudigonda et al. 2017	ConvLSTM	Atmospheric data	Trajectory	Multi-step	Batch
Gao et al. 2018	LSTM	Historical data	Trajectory	Multi-step (72 hrs)	Batch
Alemany et al. 2019	RNN	Historical data	Trajectory	Multi-step (120 hrs)	Batch
Rüttgers et al. 2019	GAN	Atmospheric image	Trajectory	Single step (6 hrs)	Batch
Kim et al. 2019	ConvLSTM	Climate data	Trajectory	Multi-step (15 hrs)	Batch
Eslami et al. 2019	CNN	Physical model outputs	Trajectory & intensity	Multi-step	Batch
Wang et al. 2020	Online linear	Physical model outputs	Trajectory	Multi-step (48 hrs)	Online
Giffard-Roisin et al. 2020	Neural network	Historical data and atmospheric image	Trajectory	Multi-step (24 hrs)	Batch

Proposed Framework: DTP

- Deep Trajectory Prediction (DTP)
  - LSTM-based framework
  - Utilizes the outputs generated from an ensemble of physical models
  - Alleviates the missing value problem
    - Temporal Decay Memory (TDM)
  - Two stages architecture
    - Model performance stage
    - Prediction stage

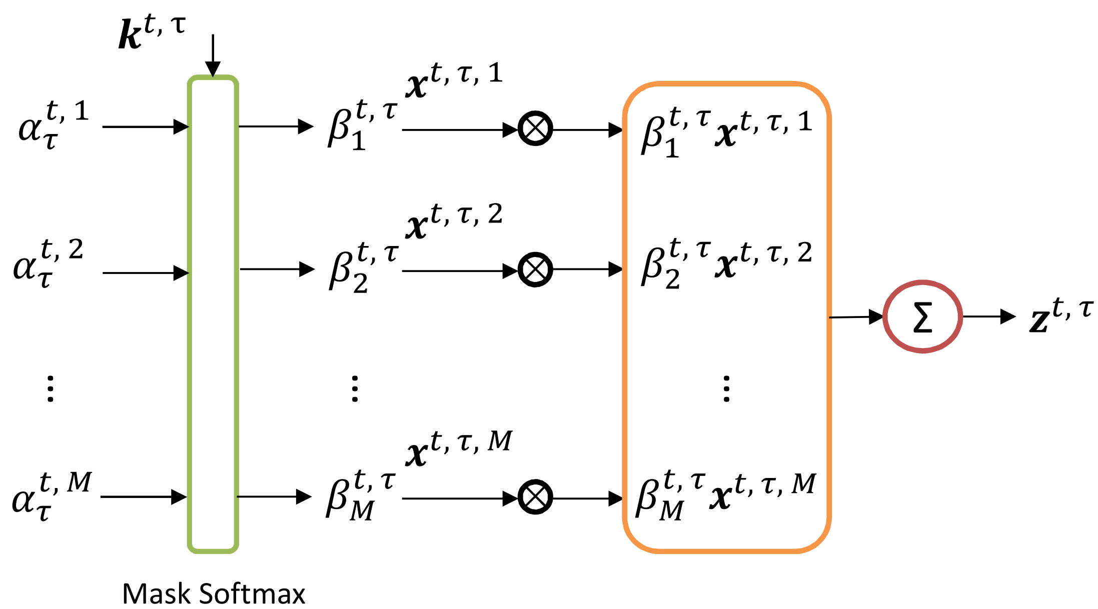
Model Performance Stage

- Let $\tilde{\mathbf{e}}^{t,m} = [e^{t-T,T,m}, e^{t-T+1,T-1,m}, \ldots, e^{t-1,1,m}]$ be the distance errors at time t associated with the multi-lead time forecasts generated by the ensemble member m.
- At time t, the model performance stage aims to output a multi-lead time performance vector $\boldsymbol{\alpha}^{t,m} = FCN(\mathbf{h}^{t,m}) \in \mathbb{R}^T$ for model m.



Prediction Stage

- The attention weight $\boldsymbol{\beta}^{t,\tau} \in \mathbb{R}^M$ for all ensemble members at time t with lead time τ can be calculated using a masked softmax layer.
- The multi-lead time predictions at time step t can be computed as a linear combination of the ensemble member forecasts with the attention weight.



Proposed Framework: ODTP

- Online Deep Trajectory Prediction (ODTP)
  - Similar network architecture as DTP
    - Fixed sequence length (T = 1)
  - Model is updated with new observation
    - Initial hidden states inherited from the previous time step
  - Backtracking and restart strategy
    - Handle the error propagation problem

Experiment Setup

- Dataset Collected
  - National Hurricane Center (NHC)
    - Best track
    - Official forecasts
  - University of Wisconsin-Milwaukee (UWM)
    - Physical model forecasts
      - 336 tropical cyclones and 27 models from year 2012 to 2020
      - Average length per tropical cyclone: 21.9 (6-hour interval)
    - Training and validation: year 2012 to 2017 (208 tropical cyclones)
    - Testing: year 2018 to 2020 (128 tropical cyclones)
- Evaluation Metric
  - Mean distance error (MDE)

https://www.nhc.noaa.gov
http://derecho.math.uwm.edu/models

Experiment Results

- Mean distance error (MDE)
  - For lead time from 12 hours to 48 hours

Method	Trajectory error (in n mi)			
Lead Time	12	24	36	48
Ensemble Mean	23.30	36.34	50.22	65.03
Persistance	34.84	88.89	155.87	229.63
LSTM	41.64	94.50	160.35	232.80
PA (online)	23.30	36.34	50.23	64.80
ORION (online)	23.37	36.36	50.21	65.00
OMuLeT (online)	**22.33**	**35.33**	48.97	63.77
DTP	23.20	36.08	49.72	64.40
ODTP (online)	22.90	35.50	**48.85**	**63.27**
NHC (gold standard)	24.59	38.49	52.17	65.74

Conclusion

- Proposed DTP framework
  - LSTM based approach
  - Long range prediction
  - Dual stage architecture
    - First stage: learns the model performance
    - Second stage: generate the predictions
- Proposed ODTP framework
  - Model is updated with new observation
  - Backtracking and restart strategy

Thank you!