EasyRain: A User-Friendly Platform for Comparing Precipitation Nowcasting Models

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Precipitation Nowcasting

To predict the future **rainfall intensity** in a **local region** over a relatively **short period** of time based on **radar echo maps**

Input Radar Echo Maps

Predicted Radar Echo Maps









Back End

Front End

Input: consecutive frames of radar echo maps **Output:** predicted future radar echo maps

Two Approaches

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- **Optical flow based models:** as represented by the Realtime Optical flow by Variational methods for Echoes of Radar (ROVER) algorithm
- **Deep learning models:** sequence-to-sequence models with novel RNN (recurrent neural network) components

Motivations

- It is not a trivial task for scientists without deep learning experience to configure and run deep learning models.
- Optical flow based methods deliver reasonable performance (but worse than deep learning methods) without the need of model training
- The performance of optical flow based methods are highly sensitive to model parameters which require a lot of empirical knowledge to optimize

EasyRain: a platform with a user-friendly web interface to help users without domain knowledge (in deep learning and/or meteorology) to efficiently build deep learning and optical flow based models, and to compare their performance

ConvLSTM & ConvGRU: extending RNN (e.g, LSTM, GRU) to have convolutional structures in both the input-to-state and state-to-state transitions so as to accommodate radar echo maps as model inputs



TrajGRU: location-variant convolutional RNN component where the recurrent connections between consecutive frames are dynamically determined **3D CNN:** faster to train than RNN models; encoding temporal information as depth of the input; convolution and pooling operations are performed spatio-temporally

The EasyRain Framework



Deep Learning Models Supported



GUI for Training

Qualitative: EasyRain allows users to view a sequence of radar echo maps (or simply, frames) as a video; the predicted frames of different models can be juxtaposed as videos along with the video of ground-truth frames

Qualitative: each predicted frame is converted into a 0/1 matrix, and evaluated against that computed from the ground-truth frame; calculating well-established quantitative evaluation metrics: Critical Index Score CSI, Probability of Detection *POD*, and Heidke Skill Score *HSS*

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Result Comparison of Two Models

Web Interface

Frame-by-Frame Comparison

Model 2

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