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

Two Approaches

- **Optical flow based models**: as represented by the Real-time 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

The EasyRain Framework

Deep Learning Models Supported

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

Web Interface

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