Sequential Images Prediction Using Convolutional LSTM with Application in Precipitation Nowcasting

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Overview

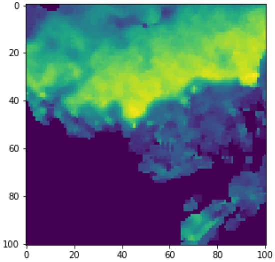
1. Introduction to Precipitation Nowcasting
2. Motivation and Model Development
3. Experiments
4. Conclusions

Overview

Goal of Precipitation Nowcasting

Goal

Give precise and timely prediction of rainfall intensity in a local region over a relatively short period of time (e.g., 0-6 hours) based on radar echo maps, rain gauge and other data.



Example of radar echo maps.

Applications:

- Provide road information under extreme weather conditions.
- Guidance for aviation at airport.
- Provide rainfall warning.

Classic Approaches

- Numerical Weather Prediction (NWP) based method.
  - Build a atmosphere model using several physical equations.
  - More accurate in the longer terms.
  - The first 2 hours of the model forecasts may not be available.
- Radar echo extrapolation based method.
  - Step 1: Optical flow estimation + Step 2: Radar echo extrapolation.
  - More accurate in the first 2 hours.
  - Example: ROVER algorithm by Hong Kong Observatory.

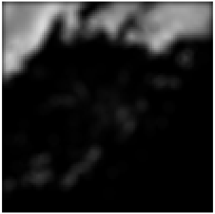
Overview

Motivation

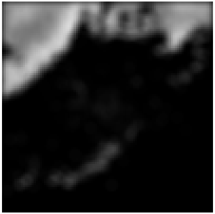
Limitation of radar echo extrapolation based method:

- Optical flow estimation & radar echo extrapolation are separated which will result in accumulative errors (i.e. Fail in decaying & growing cases of radar echo maps).

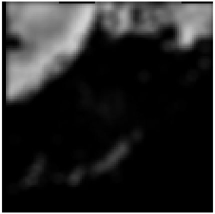
Failure example of predicting growing radar echo maps using ROVER algorithm:



First 5 input frames



15 ground truth frames



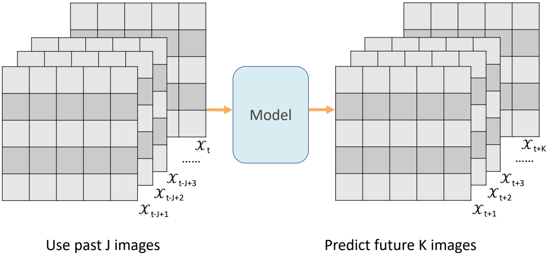
15 ROVER predictions

Machine Learning Approach

- Machine learning approach requirements:
  - Enough data.
  - End-to-end structure.
- Machine learning approach for precipitation nowcasting is not trivial:
  - Multi-step prediction
    Need a sequence of accurate rainfall intensity information at each time point in the short future.
  - Spatialtemporal data
    Take advantage of the spatial correlation within each frame (i.e. similar trends of neighbors) and temporal correlation among a sequence of input frames.

Formulation of Precipitation Nowcasting Problem

- Periodic observations taken from a dynamic system. Each radar echo map is a spatial $N_1 \times N_2$ grid. Each pixel has an integer between 0 and 255 representing the rainfall intensity.



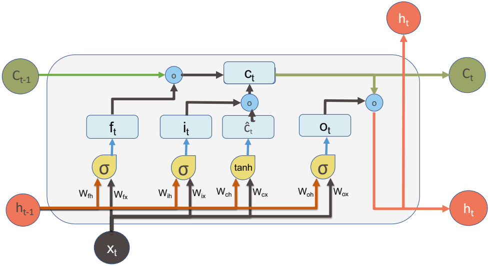
- Predict the most likely length-K sequence in the future given the previous length-J sequence:

$$\tilde{\mathcal{X}}_{t+1}, \ldots, \tilde{\mathcal{X}}_{t+K} = \underset{\mathcal{X}_{t+1}, \ldots, \mathcal{X}_{t+K}}{\operatorname{argmax}} P(\mathcal{X}_{t+1}, \ldots, \mathcal{X}_{t+K} | \mathcal{X}_{t-J+1}, \mathcal{X}_{t-J+2}, \ldots, \mathcal{X}_t)$$

How to perform multi-step prediction

Long Short-Term Memory network (LSTM) for sequential data

LSTM block at time t:



updated memory: $\tilde{\mathbf{c}}_t = tanh(\mathbf{W}_{cx}\mathbf{x}_t + \mathbf{W}_{ch}\mathbf{h}_{t-1} + \mathbf{b}_c)$

update gate: $\mathbf{i}_t = \sigma(\mathbf{W}_{ix}\mathbf{x}_t + \mathbf{W}_{ih}\mathbf{h}_{t-1} + \mathbf{b}_i)$

forgotten gate: $\mathbf{f}_t = \sigma(\mathbf{W}_{fx}\mathbf{x}_t + \mathbf{W}_{fh}\mathbf{h}_{t-1} + \mathbf{b}_f)$

new memory: $\mathbf{c}_t = \mathbf{i}_t \circ \tilde{\mathbf{c}}_t + \mathbf{f}_t \circ \mathbf{c}_{t-1}$

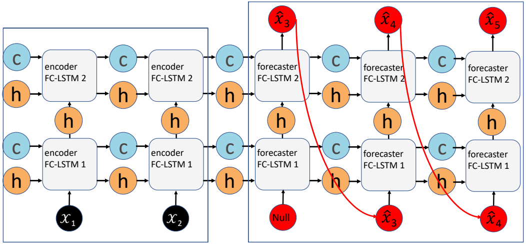
output gate: $\mathbf{o}_t = \sigma(\mathbf{W}_{ox}\mathbf{x}_t + \mathbf{W}_{oh}\mathbf{h}_{t-1} + \mathbf{b}_o)$

new hidden state: $\mathbf{h}_t = \mathbf{o}_t \circ tanh(\mathbf{c}_t)$

- LSTM with multivariate input is also called fully-connected LSTM (FC-LSTM).
- Each input x_t is in vector form.
- Memory cell c_t and hidden state h_t are also vectors of length n_{state}.

How to perform multi-step prediction

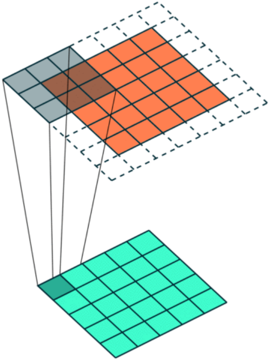
Incorporate an encoder-forecaster structure into FC-LSTM:



$$\begin{aligned}
\tilde{\mathcal{X}}_{t+1}, \ldots, \tilde{\mathcal{X}}_{t+K} &= \underset{\mathcal{X}_{t+1},\ldots,\mathcal{X}_{t+K}}{\operatorname{argmax}} P(\mathcal{X}_{t+1}, \ldots, \mathcal{X}_{t+K} | \mathcal{X}_{t-J+1}, \mathcal{X}_{t-J+2}, \ldots, \mathcal{X}_t) \\
&\approx \underset{\mathcal{X}_{t+1},\ldots,\mathcal{X}_{t+K}}{\operatorname{argmax}} P(\mathcal{X}_{t+1}, \ldots, \mathcal{X}_{t+K} | f_{encoder}(\mathcal{X}_{t-J+1}, \mathcal{X}_{t-J+2}, \ldots, \mathcal{X}_t)) \\
&\approx g_{forecaster}(f_{encoder}(\mathcal{X}_{t-J+1}, \mathcal{X}_{t-J+2}, \ldots, \mathcal{X}_t)).
\end{aligned}$$

How to deal with spatiotemporal data

Convolution for spatial correlations:



Example of sliding a 3×3 filter on a 5×5 image [1].

- The convolution of a patch of image $\mathbf{I}$ and the filter $\mathbf{K}$ is defined as:

$$\mathbf{I} * \mathbf{K} = \sum_{j=1}^{n} \sum_{k=1}^{n} x_{jk} w_{jk}.$$

- Apply zero padding to keep the convolution result as the same dimension of the input image.

[1] [1]. CNTK 103: Part D - Convolutional Neural Network with MNIST. https://cntk.ai/pythondocs/CNTK_103D_MNIST_ConvolutionalNeuralNetwork.html

How to deal with spatiotemporal data

- We lose spatial information since FC-LSTM flattens all inputs into vectors.
- Add convolution to FC-LSTM $\Rightarrow$ Convolutional LSTM.

FC-LSTM

$$
\begin{aligned}
\tilde{\mathbf{c}}_t &= tanh(\mathbf{W}_{cx}\mathbf{x}_t + \mathbf{W}_{ch}\mathbf{h}_{t-1} + \mathbf{b}_c) \\
\mathbf{i}_t &= \sigma(\mathbf{W}_{ix}\mathbf{x}_t + \mathbf{W}_{ih}\mathbf{h}_{t-1} + \mathbf{b}_i) \\
\mathbf{f}_t &= \sigma(\mathbf{W}_{fx}\mathbf{x}_t + \mathbf{W}_{fh}\mathbf{h}_{t-1} + \mathbf{b}_f) \\
\mathbf{c}_t &= \mathbf{i}_t \circ \tilde{\mathbf{c}}_t + \mathbf{f}_t \circ \mathbf{c}_{t-1} \\
\mathbf{o}_t &= \sigma(\mathbf{W}_{ox}\mathbf{x}_t + \mathbf{W}_{oh}\mathbf{h}_{t-1} + \mathbf{b}_o) \\
\mathbf{h}_t &= \mathbf{o}_t \circ tanh(\mathbf{c}_t)
\end{aligned}
$$

Input and state at a time step are all flattened as 1D tensors.

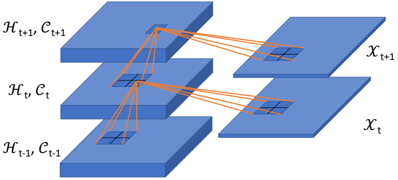
Convolutional LSTM (ConvLSTM)

$$
\begin{aligned}
\tilde{\mathcal{C}}_t &= tanh(W_{xc} * \mathcal{X}_t + W_{hc} * \mathcal{H}_{t-1} + b_c) \\
i_t &= \sigma(W_{xi} * \mathcal{X}_t + W_{hi} * \mathcal{H}_{t-1} + b_i) \\
f_t &= \sigma(W_{xf} * \mathcal{X}_t + W_{hf} * \mathcal{H}_{t-1} + b_f) \\
\mathcal{C}_t &= f_t \circ \mathcal{C}_t + i_t \circ \tilde{\mathcal{C}}_t \\
o_t &= \sigma(W_{xo} * \mathcal{X}_t + W_{ho} * \mathcal{H}_{t-1} + b_o) \\
\mathcal{H}_t &= o_t \circ tanh(\mathcal{C}_t)
\end{aligned}
$$

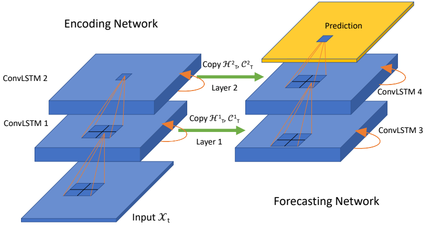
Input and state at a time step are 3D tensors. Convolution is used in both input-to-state and state-to-state transitions.

ConvLSTM Encoder-Forecaster network

Inner structure of ConvLSTM



Final model: stacked ConvLSTM encoder-forecaster network:



Training process:

- Cost function: Pixel-wise MSE.
- Back-Propagation Through Time (BPTT) to derive the derivatives of cost function with respect to each parameter & Adam optimization algorithm to update parameters.
- Apply early-stopping on validation set to avoid overfit on training set.

Overview

Experiments

- Experiment on a synthetic Moving-MNIST data.
  - Gain basic understanding of ConvLSTM.
  - Test the effectiveness of ConvLSTM on synthetic data.
- Experiment on the real-life Shenzhen radar echo data.
  - Test if the ConvLSTM based model is effective for the precipitation nowcasting task.

Moving-MNIST data

- 2 digits bouncing within 5 pixels each time step inside a 64×64 box.
- 8000 training sequences + 2000 validation sequences + 2000 test sequences, first 7 frames for input and last 7 frames to predict.
- Performance of different models:

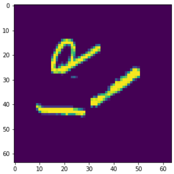
Model	# parameters	MSE_{train}	MAE_{train}	MSE_{val}	MAE_{val}
2-layer FC-LSTM $-2048-2048$	92,295,168	814.40	10.12	838.52	9.92
1-layer ConvLSTM $(5 \times 5) - 5 \times 5 - 128$	3,311,617	694.40	7.82	734.76	8.14
2-layer ConvLSTM $(5 \times 5) - 5 \times 5 - 64$ $-5 \times 5 - 64$	2,475,521	631.53	7.10	659.33	7.32
3-layer ConvLSTM $(5 \times 5) - 5 \times 5 - 64$ $-5 \times 5 - 32 - 5 \times 5 - 32$	1,858,049	582.79	6.62	625.55	6.90

Table: '-5×5' is the filter size for the state-to-state transition. '-128', '-64' and '-32' represent number of filters for the hidden states and memory cells in each layer. '(5×5)' means the filter size for the input-to-state transition.

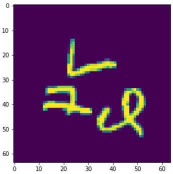
- Shallower ConvLSTM based network with much less parameters outperforms the deeper FC-LSTM based method.
- Deeper ConvLSTM based network provides better forecast.

Out-of-domain case

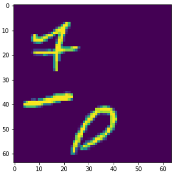
Apply the best trained 3-layer ConvLSTM model on new generated data with 3 moving digits. Use the first 7 frames as input and last 7 frames as ground truth.



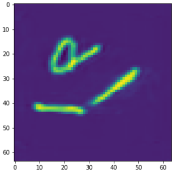
ground truth



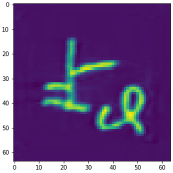
ground truth



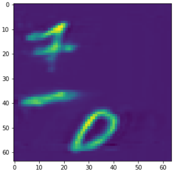
ground truth



prediction



prediction



prediction

Shenzhen radar echo maps data

- 10000 sequences. Each sequence has 15 frames. First 8 frames for input and last 7 frames to predict.
- Each radar echo map is a 101×101 grid. Each pixel value is a transformation of rainfall intensity in an area of 1 km^2.
- Select 5485 most variant sequences with correlation between the first frame P and last frame Q less than 0.75.

$$correlation(P, Q) = \frac{\sum_{i,j} P_{i,j} Q_{i,j}}{\sqrt{(\sum_{i,j} P_{i,j}^2)(\sum_{i,j} Q_{i,j}^2)} + \epsilon}$$

- To have enough data, we rotate the all frames counter-clockwise by 90 degrees and reverse the order of every sequence. We add the new data to have 10970 sequences in total.
- 6582 training sequences + 2194 validation sequences + 2194 test sequences.

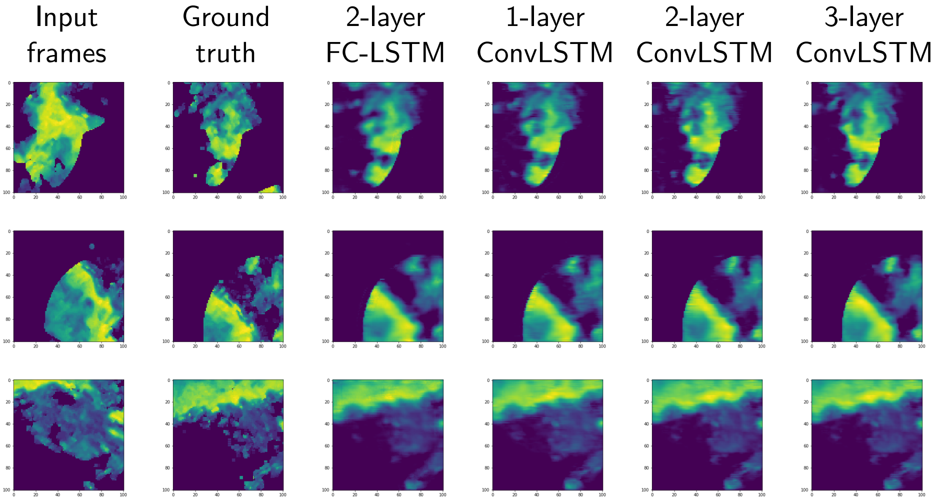
Shenzhen radar echo maps data

Performance of different models:

Model	# parameters	MSE_{train}	MAE_{train}	MSE_{val}	MAE_{val}
2-layer FC-LSTM $-2048-2048$	154,816,473	699.87	13.78	754.69	14.77
1-layer ConvLSTM $(3\times3)-3\times3-128$	1,191,937	656.74	12.39	688.59	13.71
2-layer ConvLSTM $(3\times3)-3\times3-64$ $-3\times3-64$	894,465	625.97	12.19	655.87	13.17
3-layer ConvLSTM $(3\times3)-3\times3-64$ $-3\times3-32-3\times3-32$	670,209	609.33	11.81	638.69	12.83

- The ConvLSTM encoder-forecaster network still outperforms the FC-LSTM encoder-forecaster network for this more complex task.
- Deeper ConvLSTM is more effective in precipitation nowcasting.

Shenzhen radar echo maps data



Overview

Conclusions

- ConvLSTM encoder-forecaster network breaks the limitation of classic radar echo extrapolation based method by predicting the decaying and growing radar echo maps successfully.
- ConvLSTM outperforms FC-LSTM in capturing spatiotemporal correlation by adding convolutional operation in the input-to-state and state-to-state transitions.
- Deeper ConvLSTM encoder-forecaster network provides better forecasts.
- The predicted images become more and more blurred as time step increases.