CS230: PRECIPITATION NOWCASTING USING DEEP LEARNING TECHNIQUES

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Video Link: https://youtu.be/G-aENwYe3N8

ABSTRACT
Nowcasting Precipitation is gaining traction in the artificial intelligence community. There are many neural network techniques already tried, therefore this work explores different deep learning architectures by combining CNN and LSTM neural networks, using a radar echo dataset. We have developed three models with different architectures and tested them against the synthetic moving MNIST dataset, prior to validating on precipitation nowcasting and concluded that stacked ConvLSTMs with residual input gives satisfactory results.

INTRODUCTION
We aimed to predict the sequence of Radar images, given a sequence of input frames.
- **Input**: A sequence of consecutive 6-minute interval Radar echo frames.
- **Model**: Using Convolutional and LSTM layers to deal with the spatio-temporal structure and encoding-forecasting architecture to make the predictions.
- **Output**: Prediction of 6-10 images which translate to 36 mins- 1 hour in the future.

EXPERIMENTS ON MOVING-MNIST DATASET
We started to test different deep neural network architectures on Moving-MNIST dataset where we tried to predict one time step ahead, four step ahead, and eight time steps ahead.

RESULTS AND EVALUATION
SSIM (Structural Similarity Index): Measures perceptual difference of two similar images x and y.
FAR (False Alarm Ratio) = False Positive / (True Positives + False Positives + smooth factor), give a measure of reliability.
POD (Probability of Detection, or Hit Rate) = (True Positives + smooth factor) / (True Positives +False Negatives + smooth factor) give a measure of discrimination.
A smooth factor with value=0.0001 is also used to smooth the results and avoid any potential division by zero. The evaluation of the models against these metrics is shown in the table below.

<table>
<thead>
<tr>
<th>Model Name</th>
<th>Type</th>
<th>Metrics / Skills</th>
<th>SSIM</th>
<th>POD</th>
<th>FAR</th>
<th>Epochs</th>
<th>Learning Rate</th>
<th>Batch Size</th>
<th>Loss Function</th>
<th>Optimizer</th>
<th>beta1</th>
<th>beta2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model1_x1</td>
<td>Stacked ConvLSTM</td>
<td>Accuracy</td>
<td>80%</td>
<td>40.94%</td>
<td>0.97</td>
<td>0.22</td>
<td>80</td>
<td>0.001</td>
<td>MSE</td>
<td>Adam</td>
<td>0.9</td>
<td>0.999</td>
</tr>
<tr>
<td>Model1_x2</td>
<td>Stacked ConvLSTM</td>
<td>Accuracy</td>
<td>92.00%</td>
<td>42.71%</td>
<td>0.9789</td>
<td>0.003</td>
<td>80</td>
<td>0.001</td>
<td>Logcosh</td>
<td>Adam</td>
<td>0.9</td>
<td>0.999</td>
</tr>
<tr>
<td>Model1_x3</td>
<td>Encoder-Decoder</td>
<td>Accuracy</td>
<td>91.95%</td>
<td>43.62%</td>
<td>0.2</td>
<td>0.822</td>
<td>25</td>
<td>0.1</td>
<td>mse</td>
<td>Adam</td>
<td>0.9</td>
<td>0.999</td>
</tr>
</tbody>
</table>

Figure 6: Evaluations

RADAR DATASET AND FEATURES
The dataset we used is publicly available on Harvard Dataverse and is from radar echoes captured from the NEXRAD radar located in Pudong, Shanghai.

METHODS & ALGORITHM
To tackle the problem of precipitation nowcasting we used Convolutional LSTM architecture. Architecture based on stacked ConvLSTMs:
- Convolutions capture the spatial features,
- LSTM capture the temporal dimension.

We used this architecture for both Moving MNIST and Radar datasets. Our model takes as input not just the current input example but also the historical perceived input. The model will preserve information from sequence images that has passed through it using the hidden state.

REFERENCES

FUTURE RESEARCH
In this project we focused mainly in exploring and developing several models based on ConvLSTM architectures. For future work:
- Increasing the number of training data and incorporation of additional input dimensions.
- Implementing U-NET architecture as they can address the blurriness of ConvLSTMs.

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