Forecasting Precipitable Water Vapor Using LSTMs

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Table of contents

1. Dataset
   - Visualization
   - Pre-Processing

2. LSTM Model

3. Training
   - Training Settings
   - Learning Rate Schedule
   - Training Loss

4. Results
   - Forecasting
   - Baseline Comparison
Introduction

- Forecasting GPS-based PWV values is significantly helpful in forecasting rainfall events.
- GPS-based PWV values are calculated from the Zenith Wet Delay (ZWD) by analyzing GPS signal strength.\(^1\)
- Data was collected at 5-minute resolution (Singapore, 2010).
- LSTM is already proved effective in many time-series forecasting applications.

PWV Data
Windowing the Dataset

- Extract sections with no missing values
- Make windows for Neural Network training
- Assign first 80% windows to training split and keep rest for testing

Consider a section of 100 data points. We keep 48 continuous points for input window and the immediate next point for output.
LSTM Network Model for PWV Forecasting
Training Settings

- Environment: Google Colaboratory (w/GPU)
- Library: Tensorflow 2.2 (Keras)
- Optimizer: Adam ($\eta, \beta_1 = 0.9; \beta_2 = 0.999; \varepsilon = 10^{-7}$)
- Loss: Huber Loss ($\delta = 1$)
- Batch Size: 32
- Learning Rate: $\eta = \begin{cases} 10^{-4} \times 10^{epoch/20} & \text{if } \eta < 10^{-2}, \\ 10^{-2} & \text{otherwise.} \end{cases}$
Identifying Learning Rate

![Graph showing the relationship between learning rate and Huber loss.](image)

- **Dataset**
- **LSTM Model**
- **Training Results**
Training Loss

![Graph showing the training loss over epochs](image)
Forecasting in Future

- Recursively call trained neural network
- Add the previously predicted value as last element of input sequence
- Remove the first element of the input sequence

Forecasting 15 minutes in future given 4 hours of PWV history.
Forecasting Results #1

- **PWV Value (in mm)**
- **Given Past Data**
- **Naive Method Forecast**
- **Average Method Forecast**
- **DNN Model Forecast**
- **Actual Data**

**Dataset**

**LSTM Model**

**Training**

**Results**

**APS/URSI2020 Montréal** Forecast_PWV-LSTM
Forecasting Results #2

- Given Past Data
- Naive Method Forecast
- Average Method Forecast
- DNN Model Forecast
- Actual Data

Timestamp:
- 26-11-10 23:00:00
- 27-11-10 00:00:00
- 27-11-10 01:00:00
- 27-11-10 02:00:00
- 27-11-10 03:00:00
- 27-11-10 04:00:00

PWV Value (in mm):
- 62
- 61
- 60
- 59
- 58
- 57
- 56
- 55
- 54
Comparison with Baselines

RMSE (mm) for different methods & lead-times

<table>
<thead>
<tr>
<th>Lead-time</th>
<th>DNN Model</th>
<th>Naive Method</th>
<th>Average Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 min</td>
<td>0.0978</td>
<td>0.1330</td>
<td>1.4212</td>
</tr>
<tr>
<td>10 min</td>
<td>0.1966</td>
<td>0.2581</td>
<td>1.4532</td>
</tr>
<tr>
<td>15 min</td>
<td>0.3005</td>
<td>0.3704</td>
<td>1.4854</td>
</tr>
</tbody>
</table>

- **Naive Method**: Also called as Persistence Method. Copies the last encountered data from history to the prediction.
- **Average Method**: Averages all the values from available history to predict the future value.
Comparison with Baselines - 15 minutes in Future

- Actual Data
- Naive Method Forecast
- Average Method Forecast
- DNN Model Forecast
RMSE Comparison for Different Lead-Times

![Graph showing RMSE comparison for different lead-times with lines for Naive Method, Average Method, and DNN Model.](image)
Conclusion

• Suggested LSTM network model is a potentially good candidate to perform time series forecasting of PWV values
• It can capture trends while forecasting PWV values
• Good accuracy achieved, especially for smaller lead times (upto 30 minutes in future)

Future work:

• Comparison with other state-of-the-art approaches for PWV forecasting
• Using other weather variables and images from whole sky imagers to improve prediction accuracy