DSA5204 Project Proposal: Can Time Series Imaging Improve Modeling of Temporal Dependencies?

Project Group 8

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1 Introduction

Lai et al. (2017) [1] introduced LSTNet as a novel deep learning framework specifically designed for multivariate time series forecasting. LSTNet was developed to overcome the shortcomings of traditional methods in time series forecasting, such as Autoregressive models and Gaussian processes, which often fail to capture long- and short-term patterns in time series data. By utilizing a combination of Convolutional and Recurrent neural networks, Lai et al. demonstrated the effectiveness of LSTNet in capturing the temporal dependencies in multivariate time series data through significant performance improvements over several state-of-the-art benchmarks.

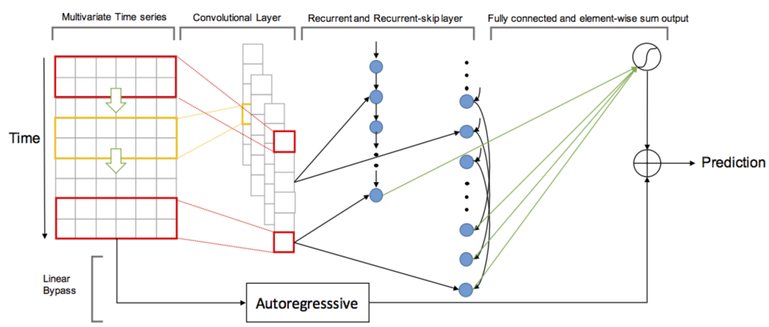

Figure 1: Model architecture of LSTNet for Multivariate Time Series Forecasting

Model Architecture

The model architecture for LSTNet can be decomposed into the following 5 components:

1. **Convolutional Component** - The first layer of LSTNet is a convolutional network without pooling, which aims to extract short-term patterns in the time dimension as well as local dependencies between variables.
2. **Recurrent Component** - The recurrent layers are designed to memorize historical information and hence be aware of relatively long-term dependencies. Gated Reccurent Unit (GRU) is adopted for this layer.
3. **Recurrent-skip Component** - Alleviate vanishing gradient problem preventing GRU from capturing very long-term correlations.
4. **Temporal Attention Layer** - Attention mechanism for nonseasonal time series prediction. Intuitively, the attention mechanism aims to select the useful information across the various feature time series data for prediction.
5. **Autoregressive (AR) Component** - Scale of input time series signals changing in non-periodic manner, thus affecting forecast accuracy of neural network models in general. AR is generally robust to scale changes.

Lai et al. further conduct an ablation study in their paper, in which each components of the LSTNet framework are removed one at a time to test their performance. The experimental results demonstrate that the removal of any components, especially the AR, Skip and CNN components caused significant performance drops. Removal of the Temporal Attention layer, however, was only observed to lead to minor reductions in performance.

Time Series Imaging

In recent years, there has been a growing interest in incorporating computer vision techniques into time series analysis and forecasting. One such approach involves transforming time series data into images and leveraging the power of Convolutional Neural Networks (CNNs) for feature recognition in time series forecasting. Wang and Oates (2015) [2] proposed two novel methods for encoding time series data as images while preserving temporal dependencies, namely Gramian Angular Summation/Difference Fields (GASF, GADF) and Markov Transition Fields (MTF). Tiled CNNs were subsequently employed for time series classification, and the proposed framework was demonstrated to achieve significant performance over state-of-the-art methods.

Project Proposal

In this project, we propose to explore if image-based encoding of time series data can effectively capture temporal dependencies in multivariate time series data, such that the model architecture of LSTNet can be simplified. In order words, this project seeks to apply time series imaging as the input, and see if such encodings can enable us to drop certain components of LSTM for model simplification. This project falls under the domain of algorithm development, and the two main publications of focus are as follows:

- Modeling Long & Short-Term Temporal Patterns with Deep Neural Networks
- Imaging Time-Series to Improve Classification and Imputation

Additional Background Reading

It would be useful to gain a better understanding of the attention mechanism in order to assess its significance in the LSTNet model, since it is observed to only lead to slight performance improvements. For this, it would be useful to refer to the seminal paper **Attention is All you Need** [3] by Vaswani et al. (2017)

We should also try to understand how Recurrent-skip works, and why it is significant as a method for alleviating vanishing gradient. This is especially so since Lai et al. noted removal of the Skip component in LSTNet caused big performance drops on some datasets. For this, we can refer to the following paper **Skip RNN: Learning to Skip State Updates in Recurrent Neural Networks** by Campos et al. (2018)

2 Scope of Work

The scope of work is as follows: Firstly, reproduction of LSTNet in TensorFlow[1]. While GAFs are available in the '*pyts*' time series imaging package, we will do a concurrent self-implementation[2] and test on the baseline datasets used by Lai et al. The next phase will be to integrate both methods, and lastly, the independent conduct of ablation studies to test our hypothesis if using image-encoding as an input can be a simpler way of capturing temporal dependencies compared to the introduction of attention or skip mechanisms. The following evaluation metrics will be adopted, in line with those used by Lai et al. and conventionally for evaluating performance in time series forecasting:

- Root Relative Squared Error (RSE):

$$\mathrm{RSE} = \frac{\sqrt{\sum_{(i,t)\in\Omega_{Test}} \left(Y_{it} - \hat{Y}_{it}\right)^2}}{\sqrt{\sum_{(i,t)\in\Omega_{Test}} \left(Y_{it} - \mathrm{mean}(Y)\right)^2}} \tag{1}$$

- Empirical Correlation Coefficient (CORR):

$$\mathrm{CORR} = \frac{1}{n}\sum_{i=1}^{n} \frac{\sum_t \left(Y_{it} - \mathrm{mean}\left(Y_i\right)\right)\left(\hat{Y}_{it} - \mathrm{mean}\left(\hat{Y}_i\right)\right)}{\sqrt{\sum_t \left(Y_{it} - \mathrm{mean}\left(Y_i\right)\right)^2 \left(\hat{Y}_{it} - \mathrm{mean}\left(\hat{Y}_i\right)\right)^2}} \tag{2}$$

Please refer to the footnotes appended to tasks for planned division of labour.

[1] Managed by Jonathan Yeo, Jonathan Lim, Lee Jian Ming
[2] Managed by Maximillian, Tan Zheng Xun

References

[1] Lai, G., Chang, W., Yang, Y. & Liu, H. Modeling Long- and Short-Term Temporal Patterns with Deep Neural Networks. (arXiv,2017), https://arxiv.org/abs/1703.07015

[2] Wang, Z. & Oates, T. Imaging Time-Series to Improve Classification and Imputation. *CoRR*. **abs/1506.00327** (2015), http://arxiv.org/abs/1506.00327

[3] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A., Kaiser, Ł. & Polosukhin, I. Attention is All you Need. *Advances In Neural Information Processing Systems*. **30** (2017), https://proceedings.neurips.cc/paper/2017/file/3f5ee243547dee91fbd053c1c4a845aa-Paper.pdf

[4] Campos, V., Jou, B., Giró-Nieto, X., Torres, J. & Chang, S. Skip RNN: Learning to Skip State Updates in Recurrent Neural Networks. *International Conference On Learning Representations*. (2018), https://openreview.net/forum?id=HkwVAXyCW