Periodic Time Series Forecasting with Bidirectional Long Short-Term Memory

Quoc-Dung Nguyen
Van Lang University
Ho Chi Minh, Vietnam
Technical University of Ostrava
Ostrava-Poruba, Czech Republic
dung.nguyen@vlu.edu.vn

Nguyet-Minh Phan
University of Information Technology
Ho Chi Minh, Vietnam
minhpn@uit.edu.vn

Ivan Zelinka
Technical University of Ostrava
Ostrava-Poruba, Czech Republic
ivan.zelinka@vsb.cz

ABSTRACT
Deep learning methods such as recurrent neural network and long short-term memory have recently drawn a lot of attentions in many fields such as computer vision, natural language processing and finance. Long short-term memory is a type of recurrent neural network capable of predicting future values of sequential data by learning observed data over time. Many real-world time series in business, finance, weather forecasting and engineering science have periodic property like daily, monthly, quarterly or yearly period and need efficient tools to forecast their future events and values. The forecasting study and tools in these fields are therefore essential and important. In this paper, we present a deep learning technique, called bidirectional long short-term memory, in forecasting time series data. The bidirectional long short-term memory model is evaluated based on the benchmark periodic time series dataset. The model performs well on the macro and industry categories and achieves average mean absolute percentage errors less than 9%. It is shown that the bidirectional architecture obtains the better results than the baseline models. We also test the model by tuning the time step parameter to evaluate how the time step length impacts on forecasting performance of the model.

CCS Concepts
• Computing methodologies → Neural networks • Applied computing → Forecasting.

Keywords
Long short-term memory; recurrent neural network; sequence prediction; time series.

1. INTRODUCTION
Time series is a sequence of data points collected sequentially in time. Predicting future values of time series is a common problem as seen in many practical fields such as finance, business planning, weather forecasting, as well as applied science and engineering. Several typical examples are forecasting the weather for the next days, daily opening and closing stock prices, electricity consumption in a household or future heart failure.

Time series introduces a dependent relationship among collected data points. Time series forecasting makes use of a prediction model to predict future values based on previous observations, as shown in Figure 1.

Figure 1. Time Series Prediction Model

Time series data often contains periodic variation and trend. A time series has a trend if its mean value is changing over time. Periodic variation, or seasonality, refers to the phenomenon where the data experiences predictive cycles that regularly recur over a time period often less than a year such as daily, weekly, monthly, or quarterly. For example, the number of visitors of a tourist attraction increases during the holidays and weekends, or swimsuit sales increase in the summer and decrease during the winter. Time series with trend or with seasonality are non-stationary.

Recurrent neural networks (RNN) are well-suited to supervised learning problems for the data having sequential nature such as text, voice, video and time series. The RNN networks are designed to capture the relation between the sequential values, hereby it can be applied to detecting periodic patterns in time series. Long short-term memory (LSTM) is an advanced version of RNN [1,2]. It is capable of handling long sequence dependence among observed inputs and therefore highly suitable for sequence prediction problem. LSTM-based methods and applications have been recently deployed in a wide range of fields such as multimedia processing [3,4,5,6], abnormal detection [7,8,9] and engineering science [10,11,12]. The bidirectional LSTM network (BiLSTM) is an extension of the original LSTM architecture where the inputs are fed into the network in two ways, one in the forward direction (from past values to future ones) and one in the backward direction (from future values to past ones).

In our previous paper [13], we have experimented the different architectures of LSTM on the benchmark time series data and shown that the bidirectional LSTM achieves the best performance among the three LSTM architectures. The LSTM models have also obtained the better results than the various baseline models on the same benchmark dataset. However, the data used in the experiments are based on only the yearly dataset, not the seasonal time series. Following that result, in this paper, we verify the bidirectional LSTM model on the time series data with seasonal characteristic in order to evaluate its performance on the periodic time series. The experimental results are compared with those of the baseline models. Additionally, we examine and analyze the performance of the proposed model based on different time step settings.

The rest of the paper is structured as follows. Section 2 presents in detail the architecture of bidirectional LSTM and its applications

DOI: http://dx.doi.org/10.1145/12345.67890