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Deep Learning-based Time Series Forecasting: Models and Applications

by Bin Wang

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Doctor of Philosophy

under the supervision of
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and Distinguished Professor Jie Lu

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CERTIFICATE OF ORIGINAL AUTHORSHIP

I, *Bin Wang*, declare that this thesis is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the School of Computer Science at the Faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of the requirements for a degree at any other academic institution except as fully acknowledged within the text. This thesis is the result of a Collaborative Doctoral Research Degree program with Southwest Jiaotong University.

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Abstract

With the advent of the era of big data and artificial intelligence, people can obtain various data and extract valuable information and knowledge through artificial intelligence technology. As a typical representative of complex data, time series modeling and forecasting have always been hot topics. In the big data environment, time series often have the characteristics of multi-source complexity, dynamic heterogeneity, uncertainty, and nonlinearity, which brings tremendous challenges to the processing and prediction of time series data. As a cutting-edge approach of artificial intelligence, deep learning has efficient automatic feature extraction and robust representation learning capabilities. Using deep learning to enhance time series forecasting performance has become an important research direction. This dissertation studies the point estimation and uncertainty quantification of time series forecasting based on deep learning methodology. This thesis achieves research contributions as follows:

(1) It proposes a point estimation network based on noisy residual connection and snapshot ensemble forecasting methods. The model reasonably simplifies the input data and introduces Gaussian noise to the residual connection to achieve regularization so that the model can significantly reduce the training time while ensuring generalization accuracy. The method of forecasting using snapshot ensemble for point estimation has also been explored. It can significantly

improve forecasting accuracy without much difference from the training time of a single model. The experiment is evaluated based on two realistic traffic flow datasets and confirms the effectiveness of the proposed methods.

(2) It develops a deep uncertainty quantification method based on the assumption of Gaussian distribution. The method employs a new likelihood loss function based on the Gaussian distribution as the training loss function of the encoder-decoder model, allowing the model to simultaneously predict the point estimation and prediction interval of multiple variables at multiple time steps. The research also reported the generalization improvement introduced by training the deep forecasting model with the likelihood loss function. This research applies the proposed method to solve a real-world weather forecasting problem. By designing an effective multi-source information fusion mechanism, it can improve the forecasting accuracy of various meteorological variables significantly.

(3) It further presents a deep uncertainty quantification method without distribution assumption. The method constructs a novel loss function without a distribution hypothesis, hence the so-called distribution-free loss function, as the objective loss function for training the encoder-decoder to model the data distribution adaptively at the training stage and then predict the point estimation and the prediction interval at the forecasting stage. The effectiveness of the proposed method is verified on three public datasets.

(4) It constructs a novel deep quantile fusion network for robust point estimation. By designing a novel loss function, the network can transform the hidden layer into a quantile layer with semantic information and take these quantiles as

the input features of the following layer to predict the target variable, thereby constructing a deep forecasting model with high accuracy and great robustness. The experiments are evaluated on eight UCI regression datasets and a time series dataset and demonstrate the effectiveness of the proposed methods.

This study focuses on time series data with characteristics of complexity, heterogeneity, abnormality, nonlinearity, and uncertainty. It discusses data preprocessing and feature fusion, proposes effective deep point estimation and uncertainty quantification methods, and applies these methods to handle practical forecasting tasks. The research works of this dissertation can promote the related research of deep learning in time series forecasting, promote the development of related industrial applications, and have both theoretical significance and application value.

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