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Organizational Impact of Spatiotemporal Graph Convolution Networks for Mobile Communication Traffic Forecasting

Pan Ruifeng
https://orcid.org/0009-0004-3014-7270
Nanchang Vocational University, China

Mengsheng Wang
https://orcid.org/0009-0001-8567-5159
Nanchang Vocational University, China

Jindan Zhang
https://orcid.org/0000-0002-1499-8460
Xianyang Polytechnic Institute, China

Brij Gupta
https://orcid.org/0000-0003-4929-4698
Department of Computer Science and Information Engineering, Asia University, Taichung, Taiwan & Symbiosis Centre for Information Technology (SCIT), Symbiosis International University, Pune, India, & Center for Interdisciplinary Research, University of Petroleum and Energy Studies (UPES), Dehradun, India, & University of Economics and Human Science, Warsaw, Poland

Nadia Nedjah
https://orcid.org/0000-0002-1656-6397
Department of Electronics Engineering and Telecommunications, Brazil

ABSTRACT

Communication traffic prediction is of great guiding significance for communication planning management and improvement of communication service quality. However, due to the complex spatiotemporal correlation and uncertainty caused by the spatial topology and dynamic time characteristics of mobile communication networks, traffic prediction is facing enormous challenges. We propose a mobile traffic prediction method using dynamic spatiotemporal synchronous graph convolutional network (DSSGCN). DSSGCN has designed multiple components, which can effectively capture the heterogeneity in the local space-time map. More specifically, the network not only models the dynamic characteristics of nodes in the spatiotemporal graph of network traffic, but also captures the dynamic spatiotemporal characteristics of the edges of mobile service data with different time stamps. The outputs of these two components are fused by collaborative convolution to obtain the prediction results. Experiments on two ground truth mobile traffic datasets show that our DSSGCN model has good prediction performance.

KEYWORDS

Communication Traffic Prediction, GNN, GCN, Self-Attention Mechanism

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INTRODUCTION

With the rapid changes in population mobility, wireless communication systems have become increasingly complex, leading to many communication problems like network lag. Therefore, the development of advanced intelligent communication systems has become an urgent need. To achieve intelligent network management, the mobile communication traffic prediction has attracted widespread attention as a fundamental research problem in the spatiotemporal data mining of communication networks.

The main challenge in predicting mobile network traffic lies in effectively modeling the dynamic spatiotemporal features of communication traffic data.

For several decades, prediction methods have evolved from traditional statistical methods to modern deep learning techniques, promoting accuracy and broadening the application of data prediction across various fields. The autoregressive integrated moving average method, widely adopted for time dimension forecasting, captures autocorrelation in sequences (Box et al., 1976). Support vector machines identify the best separating hyperplane in high-dimensional space for classification and regression tasks, demonstrating good generalization ability (Cortes & Vapnik, 1995). Random forest constructs multiple decision trees and integrates their prediction results, making it widely used in classification and regression tasks. The long short-term memory network (LSTM) improves the recursive neural network, succeeding in catching long-term dependencies and performing well in time dimension prediction (Breiman, 2001; Hochreiter & Schmidhuber, 1997). The gated recurrent unit (GRU), which mirrors LSTM, offers a simpler structure and higher computational efficiency (Cho et al., 2014). The graph convolutional network (GCN) applies convolutional operations to graph-structured data, capturing spatial relationships between nodes (Kipf & Welling, 2017), which is significant in traffic flow prediction and social network analysis. Transformer processes sequence data through a self-attention mechanism (SAM), excelling at tasks that need to capture long-term dependencies in time dimension prediction (Vaswani et al., 2017). The time fusion transformer combines the SAM and sequence modeling, focusing on multi-view time dimension prediction. Hybrid models, with combine traditional statistical techniques with machine-learning algorithms, such as combining autoregressive integrated moving average with neural networks, have been developed to improve prediction accuracy (Lim et al., 2021; Zhang et al., 1998). However, such sequence learning models have significant shortcomings in high computational training.

In the past decade, graph neural networks (GNNs) have made remarkable achievements in handling graph-structured datasets, especially in the field of spatiotemporal prediction. Notable methods, such as spatiotemporal GCN (STGCN), Graph WaveNet, and dynamic graph convolutional neural network (CNN), have gained particular prominence (Wu et al., 2019; Yu et al., 2018; Zhang et al., 2019).

STGCN captures spatiotemporal correlation by extending convolution operations to graph structured data. These methods combine GCN and unidimensional CNN to process time dimension data and handle traffic flow prediction, achieving high prediction accuracy. Graph WaveNet, a graph-based deep learning model, captures long-range dependencies in graph data. It combines extended causal convolutions and graph convolutions to model long-term dependencies without increasing computational complexity. In addition, Graph WaveNet dynamically learns graph structures through adaptive graph convolution, improving its adaptability and generalization ability.

Dynamic GCN (DGCN) focuses on the processing of dynamic graph data, allowing it to handle graph structures that change over time. This method constructs dynamic graphs and applies graph convolution operations, capturing the temporal relationships between nodes, making it widely used in traffic flow prediction. Other methods, such as temporal GCN, combines GCN and GRU to catch spatiotemporal dependencies. Attention-based spatiotemporal GCN incorporates attention mechanisms to enhance the model's ability to capture important spatiotemporal features (Guo et al., 2019; Zhao et al., 2019).

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