Advancements of Graph Neural Networks in Urban Traffic Prediction

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Abstract: Accurate traffic flow and travel speed prediction are essential for intelligent transportation systems. A particular kind of deep learning model called Graph Neural Networks (GNNs) is made especially to deal with graph-structured data, such as road networks. Road networks include intricate relationships and dependencies that can be precisely captured by them, which makes them an excellent choice for large-scale traffic flow and journey speed prediction. The use of GNNs in predicting urban traffic is reviewed in this work. We focus on methods for addressing spatiotemporal dependencies, including Spatiotemporal Graph Neural Networks (S-GNNs), Temporal Graph Convolutional Networks (T-GCNs), and attention-based techniques. Furthermore, we discuss Deep GNNs for enhancing traffic prediction accuracy, as well as the application of GNNs combined with the Internet of Things (IoT) for emergency traffic planning. Despite the substantial potential of GNNs in traffic prediction, there is a lack of systematic exploration and comprehensive analysis regarding their applicability in diverse urban environments, the optimization of real-time prediction capabilities, and their integration with urban planning and management strategies.

1 INTRODUCTION

With the rapid urbanization process, traffic congestion has emerged as a significant challenge confronting cities globally. Traffic congestion results in diminished efficiency of urban operations, increased fuel consumption, and atmospheric pollution (Sharma et al., 2023). Accurate traffic flow and travel speed prediction are paramount for the design and implementation of Intelligent Transportation Systems (ITS) (Sharma et al., 2023; Khorami et al., 2023; Piccialli et al., 2024). ITS can optimize traffic flow control systems, mitigate road congestion, enhance road usage efficiency, and foster environmental sustainability. Traditional machine learning methods have made significant contributions to traffic flow prediction, but they are not very good at capturing complex spatial and temporal interactions (Piccialli et al., 2024). One kind of deep learning model created especially to handle graph-structured data are Graph Neural Networks (GNNs). They are useful for large-scale traffic flow and road segment travel speed prediction because they can accurately reflect the intricate linkages and dependencies found in metropolitan road networks (Khorami et al., 2023; Piccialli et al., 2024).

GNNs offer an effective means to model the inherent intricate relationships and interactions within transportation networks. Among these, the temporal and spatial interdependence issues in traffic prediction are of significant importance. Luo et al. have proposed Spatiotemporal Graph Neural Networks (S-GNNs) as a traffic prediction method (Luo et al., 2024). S-GNNs investigate the nonlinear relationships between variables while concurrently accepting a variety of traffic data inputs. According to Khorami et al., the temporal and spatial interconnectedness can be captured by mixing two or more models (Khorami et al., 2023). One graph neural network model that combines a Graph Convolutional Network (GCN) and a Gated Recurrent Unit (GRU) is called the Temporal Graph Convolutional Network (T-GCN). In T-GCN, temporal dependencies are captured by the GRU and

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spatial aspects are captured by the GCN. Another example is the integration of GNNs and a Generative Adversarial Network (GAN) to achieve efficient traffic management using generative reasoning(Piccialli et al., 2024). Alourani et al. have proposed a method using a dual attention neural network to handle complex situations caused by outside factors like weather and accidents. The method uses bidirectional Long Short-Term Memory (LSTM) units to capture the temporal dependencies between features and GNNs to represent spatial features (Alourani et al., 2023). To address the issue of extracting as much effective information as possible from nodes, Huang et al. have proposed a multimodal spatiotemporal convolutional method that integrates multiple spatiotemporal modules (Huang et al., 2022).

In addition to addressing the challenges of temporal and spatial dependencies, GNNs can also be applied to other facets of traffic prediction. For example, based on the characteristics of the interconnections between roads, a deep GNN method has been proposed to optimize existing GNN models for traffic prediction (Sharma et al., 2023). For traffic prediction in scenarios with missing data, Ru et al. have proposed a method based on GNNs for traffic prediction using small sample data (Ru et al., 2020). In terms of optimizing urban emergency transportation, integrating GNNs with Internet of Things (IoT) edge computing based on dynamic graph structures can significantly enhance the accuracy of traffic prediction (Sun et al., 2022). Although GNN technology has demonstrated substantial potential in traffic prediction, there is still a dearth of systematic exploration and comprehensive analysis regarding its applicability in diverse urban environments, the optimization of real-time prediction capabilities, and its integration with urban planning and management strategies.

This article is structured in the following manner. First, we will list the uses of GNNs in intelligent transportation along with specifics of their approaches in Section 2. Next, we will examine GNNs' possible applications in intelligent transportation in more detail in Section 3 and provide a clear research framework for upcoming needs. In conclusion, Section 4 offers a synopsis of the entire piece.

2 METHOD

2.1 GNNs for Addressing Spatiotemporal Dependencies

2.1.1 Spatiotemporal Graph Neural Networks

In the study exploring the application of GNNs to urban traffic forecasting, the work of Luo et al. highlights the capability of S-GNNs in handling the heterogeneity and complexity of traffic data (Luo et al., 2024). Their study proposes a spatiotemporal graph neural network model that can accept multiple traffic data sources as input and deeply explore the nonlinear correlations among these variables. By creating a spatiotemporal directed graph, the model is able to assign distinct attention weights to neighboring area nodes of the target node in addition to capturing the sample features at each time step and aggregating the neighborhood information of nodes using graph convolution. This approach demonstrates significant advantages in improving the accuracy of both short-term and long-term traffic forecasting, particularly in reducing prediction errors, proving its effectiveness and feasibility in practical applications.

Further enhancing the performance of traffic flow forecasting models, the study by Khorami et al. introduces a Decomposed Temporal Self-Attention Multi-Layer Graph Convolutional Network (DTSA-3GCN) (Khorami et al., 2023). This research effectively addresses the issue of accuracy degradation in long-term forecasting of traditional T-GCN models by incorporating Singular Value Decomposition (SVD), Self-Attention (SA) mechanism, and Temporal Multi-Layer Graph Convolutional Networks. The model significantly improves the performance of GNNs by optimizing the adjacency matrix and utilizing low-dimensional data. Khorami et al.'s work not only showcases the significant improvement in traffic flow forecasting accuracy by deeply analyzing the spatial and temporal dependencies in traffic data but also provides new perspectives and methods for urban traffic management and planning (Khorami et al., 2023).

2.1.2 Attention Mechanisms-Based Techniques

For traffic forecasting models, the ability to consider external influencing factors, such as weather and incidents, is crucial. In the literature, Alourani et al. successfully demonstrate the significant role of dual attention mechanisms in enhancing the accuracy of traffic flow forecasting through their research (Alourani et al., 2023). Their study combines GNNs and Bidirectional Long Short-Term Memory (BiLSTM) networks, introducing a novel dual attention mechanism that focuses on capturing both the spatial characteristics and temporal dependencies of traffic data simultaneously. Specifically, the spatial attention module concentrates on analyzing the traffic flow relationships between different geographical locations, while the temporal attention module investigates the evolving traffic patterns over time. Through this approach, Alourani et al.'s model successfully improves the traffic flow prediction accuracy of specific road segments while considering the impact of weather factors, confirming the importance of dual attention mechanisms for understanding and predicting complex traffic systems (Alourani et al., 2023).

2.1.3 Multimodal Data Fusion Techniques

In recent years, multimodal data fusion techniques have shown significant promise in improving traffic forecasting models' performance. Huang et al. propose a novel traffic flow forecasting framework based on multimodal spatiotemporal convolution (Huang et al., 2022). By fusing data from heterogeneous sources (e.g., vehicle detector data, social media data), the framework deeply analyzes the relationships among different data sources using an adaptive spatiotemporal convolution module, mixed jump-diffusion Ordinary Differential Equation (ODE) spatiotemporal convolution module, and multimodal spatiotemporal fusion module, leading to more accurate predictions of traffic flow and behavior patterns. This not only provides new perspectives for urban traffic management and planning but also showcases the potential of deep learning approaches in handling complex spatiotemporal dependencies.

2.2 Deep GNNs for Enhanced Traffic Forecasting Accuracy

Faced with complex road network structures and diverse traffic conditions, simple GNN frameworks fall short in making accurate traffic predictions, leading to the proposal of Deep GNN approaches for enhanced accuracy in complex traffic forecasting. The STGGAN model was proposed by Sharma et al. for real-time traffic speed prediction (Sharma et al., 2023). The spatiotemporal properties of traffic speed data are extracted using the STGNN model using multi-level spatiotemporal graph analysis. The deep learning model, spatial feature aggregation, and feature extraction are the three main elements that make up the model. There are numerous noteworthy aspects in the STGNN model. First of all, it captures intricate interactions between geographical and temporal aspects by integrating graph structures and spatiotemporal data. Second, it uses a Gated Recurrent Unit (GRU) layer to efficiently capture temporal correlations in traffic data. Finally, a Graph Attention Network (GAT) layer is incorporated into the model to represent spatial dependencies and make use of previous road network knowledge.

Furthermore, incorporating attention mechanisms into GNNs, also a type of Deep GNN approach, can enhance traffic forecasting accuracy. Based on GPS data from taxis, Ru et al. present a model for anticipating traffic operational conditions in urban road networks by employing a limited number of crucial segments (Ru et al., 2020). To determine the crucial sections and attain high prediction accuracy, the model makes use of a graph neural network with an attention mechanism. The suggested approach lowers the price of gathering traffic data and is economical. The suggested model examines how each section contributes to the prediction of vehicle speed using the attention mechanism. The attention coefficients are calculated using the softmax function. The model also incorporates a graph attention network to consider the correlation between segments in the road network.

2.3 GNNs Combined with IoT for Emergency Traffic Planning

The Internet of Things (IoT) plays a pivotal role in urban traffic management, with a vast number of IoT devices deployed across cities, capable of collecting massive amounts of traffic data. The combination of GNNs and IoT has a wide range of applications, particularly in IoT system intrusion detection (Zhou et al., 2022). Sun et al. design a dynamic graph structure that works in conjunction with a GNN algorithm, enabling rapid traffic forecasting using small and local data collected in real-time from IoT devices in urban areas, thus addressing the issue of emergency traffic planning in cities (Sun et al., 2022). This dynamic graph structure is capable of expanding inside a local mobile communication network, taking into account both temporal and geographical information. It uses a graph representation of the road network, with nodes standing in for intersections and edges for roads. Each node and edge are timestamped, indicating the time of traffic flow data collection. To capture dynamic changes in traffic flow, the approach employs time series modeling techniques. It represents historical traffic flow data of each node as a time series and uses GNNs to learn patterns in the time series. This method's primary benefit is its compatibility with Internet of Things devices, utilizing small and local datasets for real-time forecasting. This is particularly useful in small-scale cities while also being scalable to larger datasets and more complex traffic networks.

3 DISCUSSIONS

Although GNNs excel at capturing the complex temporal and spatial relationships in traffic networks, leading to improved prediction accuracy and reduced data usage costs, particularly in large and medium-sized cities, the application of GNNs in traffic prediction is not without its challenges. Firstly, GNN models are often black-box models, making it challenging to interpret the reasons behind their predictions. This can be a problem for safety-critical applications, where it is important to understand how the model makes its decisions. Secondly, the performance of GNN models can be limited and affected by imbalanced data in urban traffic, such as the occurrence of localized peak traffic flow on urban roads. Thirdly, GNN models are sensitive to changes in the graph structure, which can lead to performance degradation when the traffic network changes. There are also several other factors that need to be considered when applying GNNs to traffic prediction and intelligent traffic management. In addition to the urban Internet of Things as the basic infrastructure of smart cities, to maximize the synergistic effect, it is imperative to investigate the most effective ways to integrate GNN models with other technologies.

Despite the challenges and limitations discussed above, GNNs hold great promise for revolutionizing traffic prediction and intelligent traffic management. Future research should focus on developing interpretable GNN models, exploring data-efficient GNN models, and investigating the integration of GNNs with other technologies. Interpretable GNNs can help to address the black-box nature of GNNs by providing explanations for their predictions. The predictions of GNN models can be explained by interpretability techniques like Shapley Additive Explanations (SHAP) or Local Interpretable Model-Agnostic Explanations (LIME). A unique machine learning strategy called domain adaptation seeks to enhance the model's performance on the target domain by adjusting the difference between training and testing data from various distributions (Farahani et al., 2021). Therefore, combining GNN with domain adaptation will help address the limitation of GNN models due to the imbalanced distribution of traffic data. Integrating GNNs with other technologies such as attention mechanism (Qiu et al., 2022) can help to further improve the performance and robustness of traffic prediction and intelligent traffic management systems. For example, GNNs can be integrated with reinforcement learning to develop adaptive traffic signal control systems, or with generative adversarial networks to generate realistic traffic scenarios for training and testing. In addition, graph structure adaptive GNN models will also be an important research direction in the future. Graph structure adaptive GNN models enable them to handle changes in the graph structure. This can be achieved by using dynamic graph convolution or graph attention mechanisms, which can capture changes in the graph structure and adjust the model weights accordingly. The optimization directions mentioned above for GNNs will enable them to play a more crucial role in future urban traffic prediction.

4 CONCLUSIONS

This paper provides a comprehensive review of recent research on the application of GNNs in urban traffic prediction, demonstrating the unique advantages and potential of GNN technology. Our primary contributions lie in exploring and analyzing different GNN models, such as S-GNNs, Deep GNNs, and GNNs integrated with the IoT, revealing the potential and effectiveness of these models in improving the accuracy of urban traffic prediction and optimizing urban emergency traffic systems. GNNs are capable of effectively capturing the complex dependencies in traffic data, enhancing the accuracy of traffic flow and vehicle speed predictions. Particularly, when considering the spatial characteristics of road networks and the temporal variations of traffic flow, GNNs demonstrate their unique advantages. However, despite the significant potential shown by GNNs in urban traffic prediction, our research also highlights their limitations in interpretability, applicability, and other aspects. We believe that future research should focus on optimizing the real-time prediction capabilities of GNN models, improving the interpretability of models, and exploring their application in a wider range of urban environments. Additionally, integrating the latest Internet of Things technologies to further enhance the effectiveness of GNNs in urban emergency traffic planning is also an important research trend.

AUTHORS CONTRIBUTION

All the authors contributed equally, and their names were listed in alphabetical order.

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