

A Survey on Graph Neural Networks in Intelligent Transportation Systems

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Intelligent Transportation System (ITS) is vital in improving traffic congestion, reducing traffic accidents, optimizing urban planning, etc. However, due to the complexity of the traffic network, traditional machine learning and statistical methods are relegated to the background. With the advent of the artificial intelligence era, many deep learning frameworks have made remarkable progress in various fields and are now considered effective methods in many areas. As a deep learning method, Graph Neural Networks (GNNs) have emerged as a highly competitive method in the ITS field since 2019 due to their strong ability to model graph-related problems. As a result, more and more scholars pay attention to the applications of GNNs in transportation domains, which have shown excellent performance. However, most of the research in this area is still concentrated on traffic forecasting, while other ITS domains, such as autonomous vehicles and urban planning, still require more attention. This paper aims to review the applications of GNNs in six representative and emerging ITS domains: traffic forecasting, autonomous vehicles, traffic signal control, transportation safety, demand prediction, and parking management. We have reviewed extensive graph-related studies from 2018 to 2023, summarized their methods, features, and contributions, and presented them in informative tables or lists. Finally, we have identified the challenges of applying GNNs to ITS and suggested potential future directions.

CCS Concepts: • **Computing methodologies** → **Neural networks**; **Learning latent representations**.

Additional Key Words and Phrases: Traffic Flow Prediction, Graph Neural Network, Spatio-temporal Analysis

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1 Introduction

As cities expand and transportation systems develop, some transportation system problems are gradually exposed, including traffic congestion, environmental pollution, and a growing number of traffic accidents. In order to alleviate the problems mentioned above and improve traffic flow, plan routes, and increase transportation safety, the Intelligent Transport System (ITS) was proposed over five decades ago in the U.S. [169]. ITS is an intelligent system covering many areas, including traffic forecasting, autonomous vehicles, traffic signal control, etc. It is worth noting that traffic forecasting is one of the hottest research areas that attracts the most attention because of its fundamental applications in transportation domains, such as optimizing route planning, facilitating road traffic, and reducing traffic accidents. However, achieving high accuracy and confidence in these ITS subdomains still remains challenging. According to Verses et al. [147], there are many practical challenges not only in dealing with massive and noisy data but also in terms of scalability and generalization. Therefore, efficient algorithms and scalable models should be further developed to fully harness the potential of massive data and build accurate and efficient ITS.

Over the past three decades, statistical methods, such as simple linear time series models including autoregressive integrated moving average (ARIMA) [84, 167], traditional machine learning methods including Logistic Regression (LR), Support Vector Regression (SVR), k-Nearest Neighbors (KNN) [21, 68, 170] were proposed to solve these problems. However, the proliferation of data and complex road conditions relegate traditional methods to the background. Besides, the advancements in computational techniques such as graphical processing units (GPU) make deep machine learning models phenomenal. According to the significant milestones of deep-learning-driven traffic forecasting summarized in [33], the deep-learning models for traffic forecasting have flourished since 2015, and the most popular models after 2019 are Graph Neural Networks (GNNs). The advantages of GNNs lie in not only modeling graph-based problems well but also the ability to capture the temporal-spatial dependency and represent the relations in non-Euclidean space [33, 69, 120].

After a detailed survey of the work in the field of ITS, we find that a significant portion of the studies focus on traffic forecasting. However, we believe that other domains in ITS require more attention. Moreover, while most recent research has shifted towards promising techniques like deep learning and reinforcement learning, GNNs still need more attention and applications. Considering the graph structure of traffic networks and the advantages of GNNs mentioned above, we believe they are the next emerging and highly competitive solution for ITS. We mainly investigated papers based on GNNs in the field of ITS published between 2018 and 2023 and made a detailed summary. We have also identified research challenges faced in the field of ITS and suggested some potential future directions for applying GNNs.

Following the above discussion, our main contribution can be summarized as follows:

- *Comprehensive Review.* Extensive research work or surveys from 2018 to 2023 for Intelligent Transportation System are reviewed in detail. This research covers general and typical research fields ITS instead of focusing on traffic forecasting. Moreover, we elaborate on the studies reviewed, summarize their methods and challenges, and form informative tables and lists.
- *A Comprehensive Taxonomy.* We carefully categorized the researched studies according to different criteria based on the research field related, graph methods utilized, and domain-specific challenges encountered, which help readers fully understand each domain in ITS from multidimensionality.
- *Challenges and Future Directions.* After a comprehensive review, we summarize the significant challenges faced when applying GNNs to ITS and suggest potential future directions, which is beneficial for those who want to follow up and delve into this research area.

We organize the rest of the survey as follows. In section 2, we quickly review the related surveys in transportation domains and briefly introduce them. In section 3, we provide the background knowledge of ITS, graph neural networks, and problem formulation. In Section 4, we investigate and review extensive graph-based studies in six ITS domains, including traffic forecasting, autonomous vehicles, traffic signal control, transportation safety, demand prediction, and parking management. In Section 5, we summarize the challenges and potential future directions in the applications of GNNs in ITS based on the previous review results. Finally, we get the conclusion in Section 6.

2 Related Surveys

ITS have been developing since the 1970s [169] and have evolved from statistical approaches and traditional machine learning to deep and reinforcement learning methods. This section selects the most relevant, influential, and representative surveys in transportation domains, most of which were published in the last five years. We pay particular attention to approaches based on graph neural networks, for which we provide a comprehensive introduction.

In application perspective, there are various research fields in Intelligent Transportation Systems, such as traffic forecasting and autonomous vehicles. However, recent surveys have primarily focused on traffic forecasting [29, 33, 69, 70, 139, 186], in which short-term forecasting [83, 150] and traffic flow/speed forecasting have particularly received more attention. On the other hand, only a few surveys have explored other ITS domains [39, 47, 120, 147]. In a survey by Liu et al. [104], visualization charts were used to review papers within the ITS field. According to the charts, traffic flow prediction has been the most dominant research topic in traffic forecasting since 2015. From 2017 onwards, the focus has shifted towards deep learning, feature extraction, long short-term memory, spatial-temporal correlation, and other related areas.

There are two works most relevant to our work: the work of Jiang et al. [69] and Rahmani et al. [120]. The work by Jiang et al. [69] is a comprehensive review survey of graph neural networks for traffic forecasting, which summarizes the research progress on GNNs for traffic forecasting. They researched 212 articles published between 2018 and 2020, made a good problem and methods taxonomy, and collected their open-source data information and code resources. This article divides the traffic forecasting problem into four groups: flow, speed, demand, and other problems. Similarly, it divided GNNs into four groups: recurrent GNNs, convolutional GNNs, graph autoencoders, and spatial-temporal GNNs. In the following year, they continued their work. They published another survey [70], which serves as an extension of [69], in which they described the latest research progress and trends in 2022, pointed out specific existing challenges, and suggested some more informative future directions. The work by Rahmani et al. [120] is the most up-to-date and comprehensive review survey of GNN under the general ITS research fields. This article encompasses several ITS research areas, including traffic forecasting, demand prediction, autonomous vehicles, intersection management, parking management, urban planning, and transportation safety. Besides, it briefly introduced all of its research work in more detail and listed the characteristics of those works. In contrast, Jiang et al. mainly categorized articles without elaborating on them.

In chronological perspective, the surveys before 2015 mainly focus on the statistics-base methods [3, 73, 84, 85, 167, 168] and traditional machine learning models [21, 68, 144, 170]. Two of the earliest and most significant literature surveys were published by Vlahogianni et al. in 2004 and 2014 [149, 150], focusing on short-term traffic forecasting works before 2014. However, these traditional methods are not suitable for tackling new and complex transportation problems, such as extensive data, intricate road conditions, and unpredictable anomalies, due to their shallow architectures. With the advancement of theories, computational power, and hardware, several deep learning models have emerged since the mid-2010s, contributing significantly to traffic forecasting [139]. These deep learning models can be categorized into spatial dependency model

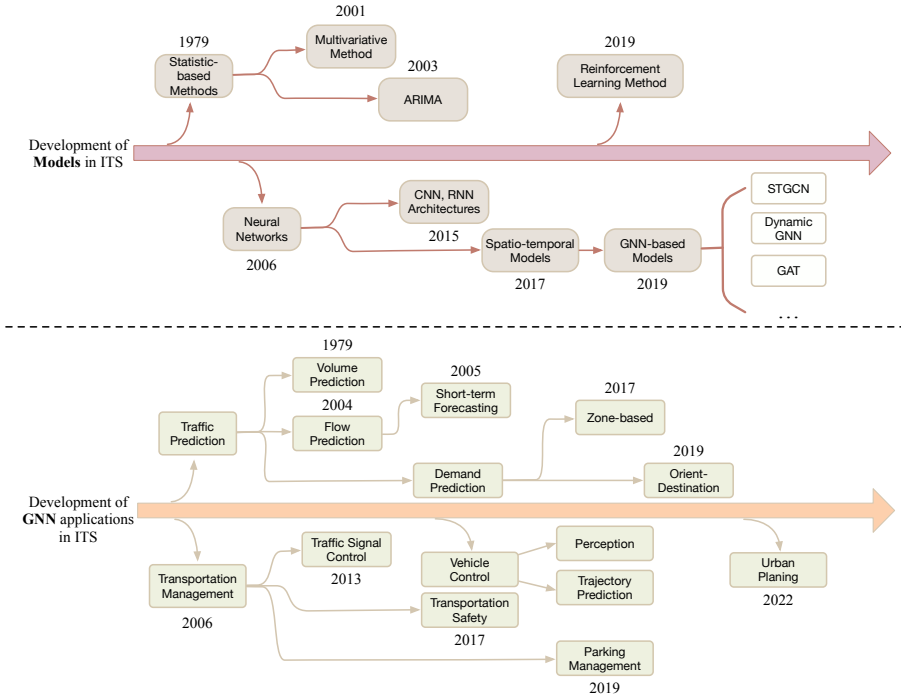


Fig. 1. Development of Models and GNN Applications in ITS.

and temporal dependency models, with Graph Convolutional Networks (GCNs) being a model that deals with spatial and temporal dependencies, making itself an excellent choice for prediction problems, according to the taxonomy of deep learning methods for traffic prediction [186].

According to another survey by Fan et al. [33] on deep learning for intelligent traffic sensing and prediction revealed that traffic forecasting models using deep learning have been growing in popularity since 2015. The most popular models since 2019 are GNNs, indicating their importance in ITS [29, 69, 70, 120]. In the last few years, researchers have been focusing on the temporal and spatial dependence of traffic data [16, 94], leading to exploring new research trends and directions.

More representative surveys. Furthermore, there are more representative surveys of GNNs in transportation domains. The paper published by Tedjopurnomo et al. [139] is considered as an early review of GNN applications in traffic forecasting. Although they mainly researched papers published between 2014 and 2019, GNNs didn't get enough attention in their paper. The survey published by Ye et al. [183] is the first of its kind that focuses on graph-based deep learning architectures for various domains of ITS, such as traffic congestion, traffic demand, transportation safety, and more. They provide a comprehensive summary of the general graph-based problem formulation and corresponding graph construction methods. Additionally, they analyze the common modules among graph-based deep learning methods, which include Recurrent Neural Network (RNN) and Temporal Convolutional Network (TCN). Furthermore, they discuss the traffic problem formulation, challenges, and research directions in detail. Regarding the spatial-temporal dependency problem, the paper published by Bui et al. [16] can be considered the first study that explores the potential solutions of Spatial-Temporal Graph Neural Networks (ST-GNN) for traffic forecasting by utilizing spatial-temporal correlation. They also propose a new taxonomy of ST-GNN by dividing existing models into four approaches: graph convolutional recurrent neural network, fully graph convolutional network, graph multi-attention network, and self-learning graph structure.

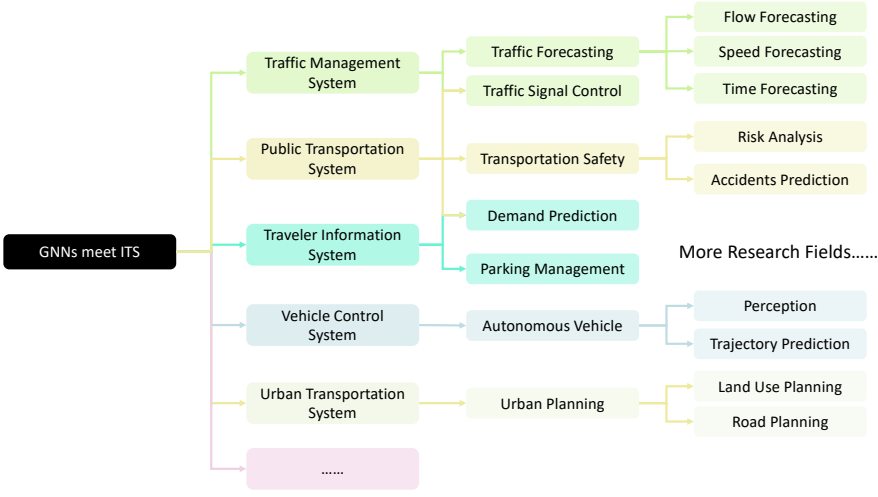


Fig. 2. Research Fields in ITS.

To this end, although GNNs have become popular in transportation domains, few studies summarize their applications in ITS. Therefore, it is crucial to conduct a comprehensive and informative review of GNNs' application in ITS. This review can fill the current knowledge gap in GNN studies within the ITS field, as well as guide the direction of future research and development.

3 Background

In this section, we will be discussing ITS, graphs, and GNNs. Firstly, we will introduce the concepts of ITS and the corresponding research fields. Following this, we will explain the fundamental concepts related to graphs, including graph data and graph types, and categorize machine learning tasks related to graphs. Finally, we will give a glance at the GNN variants and provide necessary knowledge on basic GNN models that will be referred to in the subsequent sections.

3.1 Intelligent Transportation Systems (ITS)

3.1.1 Concepts of ITS

Back to pre-1980, the concept of Intelligent Transportation Systems (ITS) was more a future-oriented idea, focused on overcoming surface transportation capacity limits [5, 169]. The emphasis was on enhancing road network efficiency via optimized traffic signals, in-vehicle navigation, and route guidance [5, 17, 116]. Notably, early ITS research recognized the significance of graph-structured data and network models [17].

With the rapid advancement of computer technology and other techniques, such as the Internet of Things (IoT), traffic data has become more easily accessible, which has led to the booming development of data-driven approaches [198]. People have begun to use real-time traffic data and information for traffic management, including road condition prediction, congestion identification, and traffic navigation etc [40, 66, 119, 125, 161, 198]. Nowadays, ITS is a continuously expanding interdisciplinary research field [99], providing innovative transportation services to enhance performance, improve travel security, and inform users. This field covers a wide range of transportation systems, including transportation management, infrastructure, policies, and control methods [198].

3.1.2 Research Fields in ITS

According to one of the most widely cited surveys on ITS [198], there are six primary sub-areas: advanced transportation management systems, advanced traveler information systems, advanced vehicle control systems, business vehicle management, advanced public transportation systems, and advanced urban transportation systems. Each sub-area has more specific research domains, as illustrated in Figure 2 [136, 161]. Our primary interest lies in technologies, particularly in applying GNN models to help solve ITS problems. As shown in Figure 2, research fields in ITS include traffic forecasting, autonomous vehicles and transportation management, traveler information analysis, urban planning, and more. In this context, we will provide detailed information about three fields.

Traffic Forecasting. Traffic forecasting is also known as traffic prediction [6, 7, 34, 188]. This problem is a very typical time-series prediction problem, predicting the most likely traffic measurements X_{t+i} in the next T time steps after time t , given the previous M time steps' traffic measurements $\{X_t, X_{t-1}, \dots, X_{t-M+1}\}$ as observations. The traffic measurements can be anything, such as speed, demand, or flow. The goal is to find the optimal prediction values $X_{t+1}^*, \dots, X_{t+T}^*$ that are as accurate as possible.

$$X_{t+1}^*, \dots, X_{t+T}^* = \arg \max_{X_{t+1}, \dots, X_{t+T}} \log P(X_{t+1}, \dots, X_{t+T} | X_t, \dots, X_{t-M+1}),$$

where $X_t \in \mathbb{R}^{N \times D}$ is the observation of all N road segments, D dimensional features each, at time t .

Transportation Management. Transportation management is a broad concept that includes various aspects of managing the transportation system, such as traffic signals, parking lots, and transportation safety [136, 161]. According to studies by Wang et al. [161], it involves at least two lines of work. Firstly, traffic prediction or forecasting is a crucial component of transportation management. Since decisions are made for the future, it is essential to have accurate predictions about traffic patterns. One way to achieve this is by acquiring reliable data about vehicle numbers and types, which can help enhance the quality of transportation management [161]. Secondly, transportation management is a decision-making problem in general. By analyzing public transportation data with the help of machine learning models, it is possible to identify patterns and rules that are not evident otherwise. This can provide valuable insights to the transportation management department to make informed decisions and improve the transportation system.

Vehicle Control. Vehicle control remains an essential part of the ITS studies. Both vehicle control system and vehicle management are included in the list of the six fundamental components in ITS [198]. The essential goal is to make wise decisions to guide the vehicles to their destinations in an automated manner, which involves identifying and registering the surrounding vehicles, as well as tracking and predicting their movements [58, 60, 64, 161].

In a way, the autonomous vehicle control system problem should be considered a decision-making problem [79, 148]. While beyond the most straightforward framework of making simple decisions according to some given conditions, vehicle control can be much more challenging due to the complexity of the input environment data [44], and decisions must be made promptly and correctly. Otherwise, we can not afford the consequences of compromising road safety [78].

3.2 General Introduction to Graphs and Graph Neural Networks

3.2.1 Graph Data and Graph Types

Graph data, as a general kind of data type that contains both entities and the relations of the entities, is typically good at representing correlations among a group of objects. Unlike basic types of data structures such as arrays or matrices, graphs are irregularly structured, with a complex topology of arbitrary size. In general, a graph \mathcal{G} can be viewed as the combination of a node-set \mathcal{V} and a corresponding edge-set \mathcal{E} . We denote it as $\mathcal{G} = (\mathcal{V}, \mathcal{E})$. The nodes are not naturally ordered. In other words, shuffling the nodes' index should not affect the results of our tasks on graphs. Nodes

in a graph can be labeled, unlabeled, or partly labeled, and they can have attributes or features. Despite their commonly shared node-link structure, they can be different types of graphs. Here are a few examples:

- **Directed/Undirected Graphs.** In an undirected graph, whenever there is an edge $(v_i, v_j) \in \mathcal{E}$ that exists, it infers that $(v_j, v_i) \in \mathcal{E}$ must hold as well, and vice versa. In a directed graph, there is no such constraint.
- **Weighted/Unweighted Graphs.** In a weighted graph, edges are assigned weight values, indicating their different importance, tightness, or other information needed. In an unweighted graph, all edges are treated equally.
- **Signed/Unsigned Graphs.** Most graphs are unsigned default, meaning all edges have positive weights if assigned a weight. In a signed graph, however, the edges are signed, meaning an edge can be either positive or negative. Sometimes, signed edges will bring more flexibility to graph design.
- **Static/Dynamic Graphs.** Static graphs have fixed node features, edge features, and edge connectivity that remain constant throughout. On the other hand, dynamic graphs are those whose data evolve over time, where new nodes can emerge or disappear at any time step, and new relationships can be established or terminated. Therefore, it is essential to model temporal information accurately to capture the changes over time. Normally, we represent a dynamic graph as a sequence of static graph screen-shots:

$$\mathcal{G} = \{\mathcal{G}_1, \mathcal{G}_2, \dots, \mathcal{G}_T\},$$

where $\mathcal{G}_t = (\mathcal{V}_t, \mathcal{E}_t)$, $t \in \{1, 2, \dots, T\}$ and T is the total number of time steps.

- **Homogeneous/Heterogeneous Graphs.** In a homogeneous graph, all nodes have the same set of features and can be considered to belong to the same group. All edges also represent similar meanings. For example, all nodes are road segments, and all edges are their connections. On the other hand, in a heterogeneous graph, the identity of nodes and edges can differ. For instance, some nodes may be vehicles, while others may be road segments. Similarly, some edges may represent vehicle interactions, while others may represent road connections or vehicles passing by a road segment. Some specific types of **heterogeneous graphs** can also be interpreted as **Multi-Dimensional Graphs**. These graphs include $|\mathcal{R}|$ different types of relations among the same set of nodes and separate the entire graph into $|\mathcal{R}|$ views, where each view indicates a single relation. The adjacency matrix becomes a 3-dimensional tensor $A \in \mathcal{R}^{|\mathcal{V}| \times |\mathcal{R}| \times |\mathcal{V}|}$.

3.2.2 Machine Learning on Graphs

The most common tasks to train a GNN model are classification and regression tasks. Both categories of tasks can be carried out at different levels, namely node level, edge level, and graph level [69, 120]. Other tasks, such as clustering, are more common on node-level [120]. Assuming that we express a graph as $\mathcal{G} = (\mathcal{V}, \mathcal{E})$. Different levels of tasks target different problems.

- **Node-Level Tasks.** Node-level tasks focus on solving problems using the node set $\mathcal{V} = \{v_1, v_2, \dots, v_N\}$. These tasks include classification tasks, regression tasks, and clustering tasks. Classification and regression tasks are supervised learning tasks where at least some of the nodes must have labels. In a classification task, the labels are discrete class types. For example, if every node v_i represents a road section, the class label set could be **{crowded, not-crowded}**. In a regression task, the labels are in continuous space. Following the previous example, if we use a crowdedness score $c_i \in [0, 1]$ to represent how crowded a road section v_i is, then the regression task label can be the ground-truth crowdedness c_i . Clustering tasks, on the other hand, are unsupervised, meaning that we no longer have ground-truth node-level labels.

The node-clustering task aims to partition the nodes into disjoint groups according to their similarities, assuming that similar nodes should belong to the same group [69]. Following the previous example, for all road sections v_i , if we intuitively believe that there are several types of road sections and assume that the features we captured are sufficient to reveal the underlying difference, we can try clustering algorithms and measure the outcome. Something to note is that, unlike other data types, graph nodes are not independent and identically distributed (i.e., i.i.d). We are not interested in modeling node dependencies either [49, 120].

- **Edge-Level Tasks.** Edge-level tasks include edge regression, edge classification, and link prediction [120]. Edge regression and edge classification tasks are very similar to node regression or node classification tasks. In this case, for an edge in the edge set $e \in \mathcal{E}$, we can have either a corresponding class label assignment l_e and make it possible to have a classification task. We can also have an edge feature score $f_e \in \mathbb{R}$ to measure specific properties of the edge to define an edge regression task. Link prediction is also known as relation prediction or graph completion. In a standard link prediction task, we train the model with a training graph consisting of only part of the edges $\mathcal{G}_{\text{train}} = (\mathcal{V}, \mathcal{E}_{\text{train}})$, where $\mathcal{E}_{\text{train}} \subset \mathcal{E}$, and the objective is to predict whether or not there exists a link between any two given nodes [69]. If nodes are road sections, the link prediction tasks could be used to complete the connectivity relations among them.
- **Graph-Level Tasks.** Graph-level tasks are typically not applicable on one graph \mathcal{G} . Instead, here we take every graph as a single data point and perform tasks on a data set of multiple graphs $\{\mathcal{G}_1, \mathcal{G}_2, \dots\}$. The focus is on learning a representation that effectively captures the features of the entire graph so that we can successfully perform classification, regression, or clustering tasks. However, few studies have been on graph-level tasks with ITS models utilizing GNNs [120]. Theoretically, having discrete properties for classification tasks or continuous properties for regression tasks is reasonable at the graph level. Besides, it also makes sense to cluster multiple traffic graphs into several groups.

Up till now, node-level tasks remain the main focus while using GNNs in ITS, while edge-level or graph-level tasks are of great potential [120].

GNNs have been a topic of great interest among researchers since their proposal [77]. GNNs are rooted in graph spectrum theory and are still shrouded in mystery, making them all the more fascinating from a mathematical standpoint [131]. While Graph Convolutional Network (GCN) [77] was not the first model to suggest convolution on graphs [30], it was the first one to strike a balance between efficiency and effectiveness. This discovery helped to highlight the potential of GNNs in the AI community, particularly for solving problems related to graph data.

There have been many studies on GNNs and their application in various fields, one of which is ITS. Graph data can be used to represent traffic flow data naturally. For example, we can consider a system with N road sections as $\mathcal{V} = \{v_1, v_2, \dots, v_N\}$, each represented as a node in a graph, and M links (i.e., edge set size $|\mathcal{E}| = M$) that represent the relationships between those nodes, such as connectivity. Whenever two road sections are directly connected, an edge is included in the edge set. This can be represented as $(v_i, v_j) \in \mathcal{E}$, where v_i and v_j are two road sections and \mathcal{E} is the edge set. From here, we can consider various tasks. For instance, we can classify roads or predict connectivity between different areas.

3.3 Graph Neural Networks (GNNs)

3.3.1 Definition of GNNs

Graph Neural Networks (GNNs) are specifically designed for graph data. At the input stage, these models usually assign a d -dimensional vector representation $x_i \in \mathbb{R}^d$ to each node v_i as

their features. The features can be any of the nodes' attributes. If nodes do not have attributes, to represent them in a neural network setting, we typically use one-hot embedding [77]. Then, multiple layers of message propagation and aggregation allow the nodes to influence their neighborhood. In each layer l , node v_i 's corresponding hidden representation $h_i^{(l)}$ is determined by $h_i^{(l-1)}$ and $h_j^{(l-1)}$, $\forall j \in \mathcal{N}(i)$ where $\mathcal{N}(i)$ denotes node i 's neighborhood. Typically:

$$h_i^{(l)} = \sigma \left(\text{Aggregation}(h_i^{(l-1)}, \text{MessagePassing}(h_i^{(l-1)}, h_j^{(l-1)}) | \forall j \in \mathcal{N}(i)) \right) \quad (1)$$

where $h_i^{(0)} = x_i$, σ is a non-linear activation function, and almost every GNN model has its own decision on the message-passing and aggregation algorithms [69, 71, 102, 120]. Finally, the outputs from the last layer are utilized in downstream tasks, where we can estimate the quality of the GNNs via task-specific loss functions and optimize the parameters in the models accordingly. These steps are identical to how we optimize other types of neural networks.

3.3.2 A Quick Glance at the GNN Variants

There are many different types of GNNs, and many have tried to classify them. A very popular categorization was proposed and agreed upon by previous researchers [173, 206, 217] and has been widely adopted ever since [1, 120]. However, these works have some differences. For instance, some earlier works did not consider graph adversarial networks. All in all, if we follow the latest version along this thread [120], we view the graph neural networks as those belonging to the following types in general: recurrent-based GNNs, convolutional-based GNNs, spatial-temporal GNNs, graph autoencoders, graph adversarial networks, and graph reinforcement learning.

Note that these categories of GNNs are mentioned just to organize our knowledge in a better way. They are not even mutually exclusive. For instance, spatial-temporal GNNs could also appear in the intersection of recurrent-based GNNs and convolutional-based GNNs, and graph autoencoders sometimes integrate graph convolutions units or recurrent units for better flexibility [120]. The different types of GNNs do have some different features:

- **Recurrent-Based GNNs.** Many people have become familiar with GNNs after learning about Graph Convolutional Networks (GCNs) [77], a convolutional-based GNN type. However, recurrent-based GNNs are proposed much earlier [126, 190]. Those recurrent-based GNNs use recurrent units as the combination function. Following similar notation system as in Section 3.3.1, we can describe the update rule as:

$$\begin{aligned} x_i^{(l)} &= f_w(h_i^{(0)}, \{h_j^{(l-1)} | j \in \mathcal{N}(i)\}, \{h_j^{(0)} | j \in \mathcal{N}(i)\}, \{e_{ij} | j \in \mathcal{N}(i)\}) \\ h_i^{(l)} &= g_w(x_i^{(l)}, h_i^{(0)}) \end{aligned} \quad (2)$$

where $h_i^{(0)}$ is the ground-truth properties of node i , e_{ij} is the feature of the edge between node i and j , f_w and g_w are both implemented by feedforward neural networks. This update unit is called an *encoding network* and is a recurrent neural network. Later follow-up works had different design decisions, such as CommNet [134] that neglected edge transformation, GG-NN [93] who used Gate Recurrent Unit (GRU) units [25] to implement the update rules. Some spatial-temporal GNNs might leverage RNN units to capture spatial and temporal dependencies simultaneously, which is a widespread practice in ITS studies [69].

- **Convolutional-Based GNNs.** Convolution on graph data [10] can be performed either in spectral [52] or spatial domain [221]. Spectral-based models are typically derived from the foundations of spectral graph theory, which involves using graph signal processing techniques such as eigenvalue decomposition and signal filtering. The main difference between spectral-based and spatial-based models is that spatial-based models only consider the neighborhood of a target node at once. In contrast, spectral-based approaches must compute over

the entire graph at a time. At times, the differences are subtle. For instance, the famous Graph Convolutional Network (GCN) [77] model is actually spectral-based, Approximate Personalized Propagation of Neural Predictions (APPNP) [37] and Autoregressive Moving Average Model (ARMA) [13] are spectral-based as well, while Graph Attention Network (GAT) [146], Graph Isomorphism Network (GIN) [176], Graph Sample and aggregate (GraphSAGE) [48], and Graph Attention Networks v2 (GATv2) [15], are all spatial-based [9, 205].

- **Spatial-Temporal GNNs.** The spatial-temporal GNNs [95, 210] are the most popular GNNs used in traffic-forecasting studies [69]. Some of these models [81, 188] use both the recurrent and convolutional units to capture the spatial (e.g., roads layout on map) and temporal (e.g., dynamic changes of the road condition) interdependencies simultaneously. Other models, such as Graph WaveNet [174], make good use of the Temporal Convolutional Networks (TCNs) [81], while the Spatial-temporal Graph Convolutional Network (STGCN) [188] combines graph convolution with 1D convolution, and the Temporal Graph Convolutional Network (TG-CN) [210] combines Graph Convolutional Networks (GCNs) [77] and Gate Recurrent Units (GRUs) [25]. These models are known for their ability to forecast the future of a graph sequence. Furthermore, spatial-temporal GNN models can be classified into subtypes, such as RNN-based, CNN-based, attention-based, and Feedforward Neural Network (FNN)-based spatio-temporal GNNs [69], which provide a finer granularity of categorization.
- **Graph Autoencoders.** Graph Autoencoders (GAEs) are generative graph neural network models. One famous example of a GAE is the Variational Graph Autoencoder (VGAE) [76]. Similar to other variational autoencoder (VAE) models [31], GAEs learn to convert input data into a latent representation during the encoding phase while also learning to generate new data that is similar enough to the original in the decoding phase. What makes GAEs unique is that they often use GNNs as their components, such as using GCNs as their encoder [1].

4 The Applications of GNNs in ITS

4.1 Traffic Forecasting

4.1.1 Traffic Flow Forecasting

Traffic flow forecasting is a crucial part of intelligent transportation system (ITS) [69]. It aims to predict the future state of traffic on a road network, including the volume of vehicles during a specific time period and across different segments of the transportation network. Accurate traffic flow prediction is essential in mitigating congestion, reducing travel times, enhancing road safety, and improving overall transportation infrastructure efficiency. Forecasting traffic flow helps stakeholders, such as city planners, traffic management authorities, and drivers, make informed decisions. For city planners and traffic managers, it aids in developing strategies for traffic signal control, incident management, and infrastructure development. For drivers, it provides valuable information for route planning and avoiding congested areas. Several factors can influence traffic flow, including daily commuting patterns, road conditions, weather, special events, accidents, and construction work [213]. These factors can be complex and constantly changing, making traffic flow prediction a challenging task that has been the subject of research for many years.

In the realm of traffic data analysis, various conventional methodologies have been utilized for predicting and recognizing patterns. Some of these include the k-Nearest Neighbors algorithm (kNN) [108], Vector Auto-Regression (VAR) [109], Auto-Regressive Integrated Moving Average (ARIMA) [14], and Support Vector Regression (SVR) [135]. However, these traditional methods have limitations, particularly in handling the complex spatio-temporal dynamics found in traffic data. One significant drawback of these techniques is their dependency on the assumption of data stationarity, which is often not met in real-world scenarios. Traffic patterns can be highly

Table 1. A Comprehensive Overview of Most Related Studies for Traffic Forecasting

Model	Article	Year	Task	Graph Construction	Spatial Module	Temporal Module	Summary
FPTN	[196]	2023	Flow	road network	transformer	transformer	FPTN improves traffic forecasting with sensor-based data division, triple types of embeddings, and an efficient Transformer encoder, reducing computational demands.
DyHSL	[213]	2023	Flow	learned hypergraph	HGNN	HGNN	DyHSL improves traffic forecasting with hypergraphs for dynamics and interactive convolutions for spatio-temporal relations, effective across multiple datasets.
DSTAGNN	[80]	2022	Flow	dynamic	GNN	GNN	DSTAGNN dynamically models spatial-temporal road network interactions by utilizing enhanced multi-head attention and multi-scale gated convolution.
Bi-STAT	[23]	2022	Flow	road network	transformer	transformer	Bi-STAT enhances traffic forecasting with adaptive spatial-temporal transformers, handling diverse task complexities and leveraging past data for improved prediction.
STFGNN	[89]	2021	Flow	road network	GNN	GNN	STFGNN enhances traffic forecasting by fusing data-driven temporal and spatial graphs and employing gated convolutions, effectively handling long sequences.
AGCRN	[7]	2020	Flow	generated	GCN	RNN	AGCRN enhances prediction by two adaptive modules, focusing on node-specific patterns and automatic inter-dependency learning without pre-defined graphs.
HGC-RNN	[184]	2020	Flow	road network	HGNN	RNN	HGC-RNN leverages hypergraph convolution and RNNs for structured time-series sensor network data, capturing complex structural and temporal dependencies.
STSGCN	[133]	2020	Flow	road network	GCN	GCN	STSGCN models localized spatial-temporal correlations and accounts for heterogeneities across different periods, simplifying spatial-temporal network data forecasting.
ASTGCN	[43]	2019	Flow	road network	GCN	attention	ASTGCN improve forecasting with a spatial-temporal attention mechanism and convolutions, focusing on dynamic correlations to make more accurate predictions.
LRGCN	[86]	2019	Flow	road network	RGCN	RGCN	LRGCN, designed for time-evolving graph path classification, integrating temporal dependencies and graph dynamics by relational GCN to process time-based relations.
DCRNN	[96]	2017	Flow	road network	GCN	RNN	DCRNN models forecasting as a diffusion process on directed graphs, using bidirectional random walks and an encoder-decoder architecture with scheduled sampling.
CAGRU	[75]	2021	Speed	road network	GAT	GRU	CAGRU predicts traffic speed and identifies patterns using a convolutional attention-based neural network based on traffic flow data without relying on historical speed data.
DMSTGCN	[50]	2021	Speed	learned	DGNN	DGNN	DMSTGCN learns dynamic spatial dependencies between road segments and incorporates multi-varied traffic data, capturing multifaceted spatio-temporal traffic features.
FASTGNN	[195]	2021	Speed	road network	ASTGCN	ASTGCN	FASTGNN, a federated learning framework, features a differential privacy-based method to protect topological information and an innovative aggregation approach.
-	[103]	2020	Speed	road network	GraphSAGE	-	This paper uses GraphSAGE to forecast spatially heterogeneous traffic speed and imputes missing data for segment networks with nonlinear spatial-temporal correlations.
ATT-LSTM	[172]	2020	Speed	road network	GAT	LSTM	Attention-based LSTM (ATT-LSTM), a short-term level prediction model, predicts traffic speed and imputes missing traffic data with a data preprocessing module.
GATCN	[41]	2020	Speed	road network	GAT	TCN	GATCN, a deep learning framework combining GAT and TCN, effectively learns spatio-temporal traffic flow characteristics and neighborhood information with multiple layers.
MTL-GRU	[200]	2020	Speed	road network	GNN	GRU	MTL-GRU, a multitask learning GRU model with residual mappings, selects the most informative features to enhance traffic flow and speed forecasting.
DSTL-GR	[155]	2023	Time	road network	GraphSAGE	LSTM	DLSF-GR enhances travel time prediction by considering spatial and temporal dependence, as well as exogenous variables, through a combination of GNNs and RNNs.
DeepTrans	[142]	2020	Time	road network	DCRNN	DCRNN	DeepTRANS enhances travel time estimation by incorporating traffic forecasting into an existing deep learning-based bus ETA model, improving congestion prediction.
SST-GNN	[123]	2020	Time	road network	SGNN	SGNN	SST-GNN predicts by encoding spatial correlations, using neighborhood aggregation and a spatio-temporal mechanism with position encoding for periodic patterns.
-	[110]	2019	Time	road segment	clustering	-	The model predicts bus travel times using real-time taxi and bus data, dividing routes into dwelling and transit segments with two tailored models for each.

non-stationary due to urban development, policy changes, and unexpected events. Therefore, these methods may fail to effectively capture the evolving trends and irregularities in traffic data.

The integration of deep neural networks in analyzing traffic data has led to significant advancements in recent years. Deep learning-based approaches, particularly GNNs, have proven to be highly effective in capturing the spatial and temporal correlations within traffic data. Studies Kipf et al. [77], Xu et al. [176], and others [15, 24, 37, 48, 146] have highlighted the effectiveness of GNNs in mapping the structured spatial patterns of road networks. These networks can adeptly delineate the complex interconnections and dependencies among various elements of transportation networks. Furthermore, sequential neural network models, such as RNNs, Long Short-Term Memory networks (LSTMs) [53], and GRUs [25], have proved to be highly efficient in decoding the temporal dynamics of traffic data. Their ability to process sequential information makes them particularly suitable for understanding and forecasting time-dependent traffic patterns.

The application of GNNs and RNNs provides a comprehensive approach to model traffic data, which offers improved accuracy and robustness in predicting and managing traffic conditions. The superior performance of these methods highlights the significant impact of deep learning methodologies in advancing traffic data analysis. It transitions from traditional models to more sophisticated, data-driven approaches.

Recent research has introduced various models that can effectively capture the complex interdependencies inherent in spatial and temporal data. These proposed models [43, 96, 133, 213] use advanced neural network architectures to analyze intricate patterns within traffic data, thereby significantly improving forecasting accuracy. These approaches excel in their ability to handle dynamic relationships within traffic systems sophisticatedly. These methods provide a comprehensive understanding of traffic behavior by simultaneously addressing spatial aspects (such as the

connectivity of roads) and temporal factors (like traffic flow variations over time). This dual focus enables more precise predictions essential for efficient traffic management and planning.

One line of research involves utilizing graph neural networks along with recurrent neural networks [25, 53] to capture spatial and temporal information recursively [7, 96, 184]. For instance, the Diffusion Convolutional Recurrent Neural Network (DCRNN) [96] replaces fully connected layers in the GRU[25] with diffusion convolution. Adaptive Graph Convolutional Recurrent Network (AGCRN), as described in [7], focuses on learning node-specific features and uncovering hidden inter-dependencies through an adaptive graph convolutional recurrent methodology. This approach reflects a growing tendency to tailor models to understand complex network dynamics. Furthermore, Hypergraph Convolutional Recurrent Neural Network (HGC-RNN), as explained in [184], combines hypergraph convolution with recurrent neural networks, specifically targeting traffic flow forecasting. This combination highlights the potential of integrating different neural network architectures to improve predictive accuracy.

Another line of research [43, 86, 133, 213] involves developing a large spatio-temporal graph and utilizing GNNs to capture spatio-temporal correlations. For example, the Spatial-temporal Synchronous Graph Convolutional Network (STSGCN) framework explained in [133] establishes a spatio-temporal graph structure, which is used to carry out localized graph convolution operations, resulting in enhanced data processing capabilities. Moreover, the Attention-based Spatial-temporal Graph Convolutional Network (ASTGCN) model outlined in [43] incorporates an attention mechanism within the spatio-temporal graph context, as described in [133]. This augments the model's performance by focusing on salient features. Additionally, the Long Short-Term Memory R-GCN (LRGCN) approach presented in [86] is designed to encode spatio-temporal graphs with increased efficiency, addressing the complexities inherent in such data structures.

More recently, various methods [80, 89, 213] have been proposed to learn the underlying graph structure using spatio-temporal data. For instance, Dynamic Spatial-Temporal Aware Graph Neural Network (DSTAGNN) [80] focuses on learning a spatio-temporal graph while applying multi-head attention [145] to represent dynamic spatial relevance. This method highlights the continuous evolution of graph neural networks towards more nuanced and intricate representations of spatial and temporal data interrelations. On the other hand, Spatial-temporal Fusion Graph Neural Networks (STFGNN), mentioned in [89], employs a spatial fusion graph coupled with a generated temporal graph, demonstrating the effectiveness of multi-faceted graph structures in data analysis.

With the success of transformers in many fields [51, 145, 212], researchers have used transformers to capture temporal information in conjunction with graph neural networks [48, 77] in the field of long-term traffic flow forecasting. However, using Transformer-based models for traffic flow forecasting is challenging because of the complex spatio-temporal correlations in traffic flow data. To address this issue, some well-designed methods are proposed [23, 62, 177, 196]. For instance, researchers have proposed Fast Pure Transformer Network (FPTN) and Multi-Spatial-Temporal Encoder-Decoder Model (MST-EDM) [196] based on Transformer. These methods divide traffic flow data into sequences along the sensor dimension and use a Transformer encoder to capture complex spatio-temporal correlations simultaneously. Chen et al. [23] have proposed a bidirectional spatial-temporal adaptive transformer (Bi-STAT) for accurate urban traffic flow forecasting. This model utilizes Encoder-decoder architecture with spatial-adaptive and temporal-adaptive transformers.

The diversity of these models demonstrates the breadth of innovation in this area. Each approach provides unique insights and methodologies, contributing to an extensive and more diverse toolkit for traffic analysts and urban planners.

4.1.2 Traffic Speed Forecasting

Speed is a crucial metric when it comes to monitoring traffic, with significant applicability in ITS. This metric is characterized as the average velocity of vehicles traversing a defined spatial segment within a specified interval of time. In urban areas, vehicle speed acts as an indicator of the level of traffic congestion. Accurate forecasting of traffic velocity is important for improving navigational routing and the precision of estimated arrival time in various applications.

Traffic speed forecasting and traffic flow forecasting share similar methodologies. In both areas, incorporating spatio-temporal information is crucial for optimizing model performance. Recent research in this field [41, 50, 75, 103, 114, 172, 195, 200], has effectively utilized both spatial and temporal dimensions in traffic speed data. For instance, the work of Liu et al. [103] employs the GraphSAGE model [48], a novel approach tailored for sparse network conditions, to enhance the accuracy of traffic speed predictions. This approach emphasizes the importance of spatial information in the context of sparse connectivity. Khodabandelou et al. [75] innovatively combine graph convolution techniques with attention-based gated recurrent units [25] to capture both spatial and temporal relationships within traffic speed data. This fusion approach enriches the model's understanding of complex traffic dynamics. Zhang et al. [200] introduce a multi-task learning framework that simultaneously processes traffic flow and speed data. This approach enables the model to learn from the intertwined nature of traffic speed and flow, leading to a more nuanced representation of spatio-temporal data and enhancing the predictive accuracy for both metrics.

The endeavor of traffic speed forecasting is further complicated by the issue of information scarcity, which highlights the difficulty in generating accurate predictions when faced with limited, incomplete, or sparse traffic data [57, 172]. Such scarcity can stem from various reasons, including the lack of coverage by sensor networks, the high costs associated with the deployment and maintenance of extensive traffic monitoring systems, and the challenges in collecting data on roads with low traffic volumes or in remote areas.

In response to these challenges, Liu et al. [103] have developed a technique that applies a data recovery algorithm based on identifying nonlinear spatial and temporal correlations within the road network. This algorithm helps impute missing speed data for different segments and enables traffic speed forecasting across a diverse and heterogeneous road network. Moreover, Huang et al. [57] have utilized Probabilistic Principal Component Analysis (PPCA) to model travel speeds reliably, even when data is missing from specific road segments. They have also employed spectral clustering to categorize roads with similar traffic conditions into clusters, which reduces the variability of traffic conditions within each group. This enhances predictive consistency and facilitates parallel computing to improve overall prediction performance.

Advanced computational models are used for traffic speed forecasting, which involve analyzing spatio-temporal data to provide real-time and accurate insights into traffic conditions. This is crucial for effective traffic management and planning, particularly in urban areas. Improved traffic forecasting can also greatly enhance the user experience in navigation and route planning applications, particularly in densely populated areas where traffic conditions are highly dynamic and unpredictable [69].

4.1.3 Traffic Time Forecasting

Traffic time forecasting, referred to as travel time forecasting, is closely related to traffic flow or demand forecasting. This field has evolved over time, utilizing methodologies developed for traffic flow or demand prediction. Initially, pioneering techniques like ARIMA [14] and support vector machines (SVM) [135] were used to predict traffic time. However, with the rise of deep learning, this field has significantly transformed, shifting towards spatio-temporal forecasting methods [7, 43, 133]. These advanced deep learning models are adept at analyzing massive traffic data to unravel complex patterns and intricate relationships, thereby elevating the precision and

robustness of travel time predictions. Integrating the temporal and spatial dimensions is crucial to spatio-temporal forecasting. This approach is pivotal in accounting for time-dependent changes and the interconnected nature of road networks. To achieve this, a blend of GNNs [48, 77, 176] and RNNs [25, 53, 137] is often employed. This combination effectively captures temporal sequences and spatial inter-dependencies within traffic data, offering a more holistic and accurate approach to travel time forecasting.

Exploring traffic flow forecasting methods [43, 96, 214] as a means of predicting travel times has become a promising and dynamic area of research in ITS [2, 74, 123, 142, 155]. Tran et al. [142] have taken the lead in this field by incorporating advanced traffic flow forecasting models into their travel time prediction system, called DeepTrans. Their methodology uses machine learning to examine vast datasets of historical traffic patterns, allowing for more precise travel time estimations. Diving deeper into the interplay between spatial and temporal factors, Kang et al. [74] introduced a novel spatio-temporal forecasting framework focused on the urban context. This approach can process and integrate multifaceted data streams, capturing the intricate dynamics of urban traffic. The model considers not only the physical layout of the transportation network but also the fluctuating congestion levels over time. By assimilating this spatio-temporal information, their model extracts essential representations that significantly improve the reliability of travel time forecasts.

Although traffic time forecasting and traffic flow forecasting are related, they are still two distinct areas in transportation domains. Traffic flow forecasting offers a macroscopic view, focusing on overall traffic conditions and trends across a broader area or network [96, 213, 214], which involves understanding traffic patterns, volume, and congestion across a network. On the other hand, traffic time forecasting delves into the microscopic details, emphasizing the temporal elements of travel. It provides detailed insights into the travel duration between specific locations, making it valuable for journey planning and management [12, 28, 163].

As an illustration, Ma et al.'s study [110] predicts bus travel times using fine-grained and real-time data, offering a detailed analysis of the traffic system. This approach is particularly useful for short-term predictions and immediate traffic management. Similarly, Comi et al. [28] focus on the temporal factors that influence long-term traffic predictions, incorporating spatial data into graph neural networks. This method is essential in understanding how different regions and routes interact over time, enhancing the accuracy of long-term traffic forecasts. While differing in scope and detail, both approaches are crucial for a comprehensive understanding of traffic dynamics and effective transportation planning.

4.2 Vehicle Control System

4.2.1 Perception

In the field of vehicle control systems, perception plays a vital role in identifying and categorizing objects in a vehicle's vicinity. Perception involves two critical tasks: semantic segmentation with classification and object detection with tracking [64]. For semantic segmentation, 3D data is often represented as point clouds, which can capture complex 3D shapes and their unique irregular structures. However, traditional deep learning methods usually convert point clouds into 3D voxel grids or collections of images before feeding them into deep neural networks, which may lead to information loss and computational overhead [44]. An alternative approach leverages the graph-like nature of point clouds, fueling a surge in research efforts employing GNNs to enhance the efficiency and accuracy of 3D data analysis. In the following sections, we review GNN-based methods for learning representations from point cloud data.

Graph-Based Methods in Spatial Domain. Spatial Convolutional Graph Neural Networks can be broadly characterized as propagating node features to neighboring nodes by adopting a

Table 2. A Comprehensive Overview of Most Related Studies for Autonomous Vehicles

Model	Article	Year	Datasets	GNN Module	Summary
GTNet	[218]	2023	ModelNet40, ShapeNet part	Graph Transformer	GTNet uses a Local Transformer to calculate neighboring point weights through dynamic graph-based cross-attention within domains, and a Global Transformer to expand its range using global self-attention.
MHNet	[106]	2023	ModelNet40, NTU	Spectral GNN	MHNet introduces a polynomial hypergraph filter, which dynamically extracts multi-scale node features.
DiffConv	[98]	2022	ModelNet40, Toronto3D, ShepeNet part	Spectral GNN	DiffConv uses density-dilated neighborhoods where each point's radius depends on its kernel density. It also uses masked attention to introduce task-specific learned variations to the neighborhood.
DeltaConv	[166]	2022	ModelNet40, SHREC11, ScanObjectNN, ShapeNet	Spectral GNN	DeltaConv uses a graph-based anisotropic convolutional operator by combining a set of geometric operators defined on scalar and vector fields to encode the directional information of each surface point.
3DCTN	[107]	2022	ModelNet40, ScanObjectNN	Graph Transformer	3DCTN combines convolutions and transformers to learn local and global features. It uses a multi-scale local feature aggregation block and a global feature learning block to process downsampled point sets.
Point Transformer	[209]	2021	S3DIS, ModelNet40, ShapeNet part	Graph Transformer	Point Transformer introduces an expressive transformer layer tailored for point cloud processing. It employs local self-attention and integrates vector attention to achieve elevated accuracy levels.
PCT	[42]	2021	ModelNet40, ShapeNet	Graph Transformer	Point Cloud Transformer (PCT) improves capturing local context capture within the point cloud by using coordinate-based input embedding with the help of farthest point sampling and nearest neighbor search.
CurveNet	[175]	2021	ModelNet40, ModelNet10, ShapeNet part	Spatial GNN	CurveNet enhances point cloud shape descriptors by organizing connected points through guided walks within point clouds and aggregating them to enhance their individual point-wise features.
LDGCNN	[199]	2021	ModelNet40, ShapeNet	Spatial GNN	LDGCNN is a linked dynamic graph CNN created for direct classification and segmentation of point clouds, addressing sparsity and unstructured nature. It also includes theoretical analysis and model visualization.
3D-GCN	[101]	2020	ModelNet40, ModelNet10, ShapeNet part	Spatial GNN	3D-GCN is a novel approach for processing 3D point clouds in computer vision that offers scale and shift invariance by utilizing learnable kernels and a graph max-pooling mechanism to extract robust features.
DHGNN	[36]	2019	ModelNet40, NTU	Spectral GNN	DHGNN addresses limitations in graph/hypergraph-based deep learning by dynamically updating hyper-graph structures and encoding high-order data relations through vertex and hyperege convolutions.
DGCNN	[159]	2019	ModelNet40	Spatial GNN	DGCNN, a novel neural network module dubbed EdgeConv suitable for point clouds, enhances CNN-based high-level tasks by incorporating local neighborhood information and adapting to topology.
RGCNN	[138]	2018	ShapeNet part	Spectral GNN	RGCNN directly processes point clouds, utilizing spectral graph theory and Chebyshev polynomial approximation to capture dynamic graph structures adaptively, enhancing point cloud understanding.
AGCN	[90]	2018	Sydney urban	Spectral GNN	AGCN, a flexible Graph CNN that takes data of arbitrary graph structure as input, enables task-driven adaptive graph and distance metric learning for diverse data such as molecular and social networks.
KCNet	[128]	2018	ModelNet40, ShapeNet	Spatial GNN	KCNet improves semantic learning efficiency for 3D point clouds by introducing a point-set kernel for 3D geometry and recursive feature aggregation on a nearest-neighbor graph that focuses on local structures.
Local-SpecGCN	[153]	2018	ModelNet40, McGill Shape, ShapeNet part, ScanNet Indoor Scene	Spectral GNN	Local-SpecGCN uses spectral graph convolution on local graphs and a graph pooling strategy for point cloud feature learning, enhancing feature descriptors by aggregating information from clustered nodes.
ECC	[132]	2017	Sydney Urban Objects, ModelNet10, ModelNet40	Spatial GNN	ECC adapts convolution operators for arbitrary graphs, avoiding the spectral domain, and uses specific edge labels in a vertex's neighborhood to condition filter weights, enabling diverse graph classification tasks.

convolutional kernel. This is followed by applying an activation function using a trainable weight matrix to map these features into the subsequent hidden layer[10]. In general, the attributes associated with each vertex are coordinates, laser intensities, or colors, while the attributes along each edge correspond to the geometric properties that connect pairs of connected points[44].

As a pioneering approach, Simonovsky et al. [132] introduced Edge-Conditioned Convolution (ECC) as the first graph-based method in a spatial domain. This method uses edge labels in vertex neighborhoods to compute adaptive convolution kernel weights. As a result, it allows for more effective utilization of edge information than traditional point-based convolutions. However, ECC [132] primarily relies on the inherent graph structure of the input point cloud, which limits flexibility and the ability to model non-local relations. To address this challenge, several methods [158, 159, 199] have been proposed. Dynamic Graph Convolutional Neural Network (DGCNN) [159] introduces an EdgeConv neural network architecture, which enables the segmentation of point clouds and the capture of semantically related structures. The dynamic graph representation of the point cloud learned by this approach evolves across layers and even during the same input's training phase as learnable parameters are updated. Building upon earlier developments like ECC and DGCNN, Linked Dynamic Graph Convolutional Neural Network (LDGCNN) [199] advances the capabilities of DGCNN by establishing links between hierarchical features derived from various dynamic graphs. This linkage enables the computation of informative edge vectors while simultaneously reducing the model's size.

To capture the local neighborhood structural information of a point, kernel-based approaches have been extensively explored, as highlighted in the studies [101, 128, 175]. For instance, KCNet [128] introduced a point-set kernel consisting of learnable 3D points. They employed a kernel correlation layer to determine the affinities between each data point's nearest neighbors and these point-set kernels. They also used recursive feature propagation and aggregation along the edges, which helped leverage local high-dimensional feature structures. Similarly, 3D-GCN [101] proposed deformable kernels that were designed to extract shift and scale-invariant local 3D features from point clouds. Furthermore, Xiang et al. [175] introduced a method for arranging connected points

through guided walks within the point clouds. They subsequently aggregated them to enhance their point-wise features, effectively improving the representation of point cloud geometry.

Graph-Based Methods in Spectral Domain. Spectral Convolutional Graph Neural Networks are based on spectral graph theory [27]. In this framework, graph signals are filtered through the eigendecomposition of the graph Laplacian. Regularized Graph CNN (RGCNN) [138] performs graph convolution and feature learning based on spectral graph theory. It treats point cloud features as signals on a graph and uses Chebyshev polynomial approximation for graph convolution. RGCNN adapts to the corresponding learned features by updating the graph Laplacian matrix in each layer, effectively capturing evolving graph structures during the learning process. Traditional spectral GCNs require the prior computation of graph Laplacians and pooling hierarchies for the entire graph, which can be computationally intensive. To address the above challenges arising from the diverse graph topology in data, two promising approaches have been proposed. One is Adaptive Graph Convolutional Neural Network (AGCN) [90], which enhances the generalization capacity of GCNs by incorporating a learnable distance metric to parameterize the similarity between two vertices within a graph, allowing for the dynamic construction of graphs. The other approach is Local-SpecGCN [153], which conducts spectral filtering on dynamically generated local graphs. It uses recursive clustering based on spectral coordinates to facilitate graph pooling, which enhances the learning process by mitigating point isolation. Instead of conventional max pooling, the authors devised a recursive clustering and pooling strategy that enables the amalgamation of information from nodes within clusters defined by their spectral coordinates.

Hypergraphs are increasingly attracting the attention of researchers as a tool for capturing high-order data correlations. One notable example is Hypergraph Neural Networks (HGNN) [36], which uses a hyperedge convolution operation to capture high-order data correlations and represent complex structures within point clouds. This operation aggregates node features into hyperedge features and then updates node features through hyperedge feature aggregation. Hypergraph Graph Convolutional Network (HyperGCN) [178] uses non-linear Laplacian operators [19] to convert hypergraphs into more straightforward graphs by breaking hyperedges down into subgraphs with edge weights that depend solely on their degrees. Hypergraph convolution relies on a predefined structure for propagation. To overcome this limitation, Bai et al. [8] introduced an attention mechanism for dynamic connection learning among hyperedges. This mechanism ensures that information propagates and gathers in graph regions relevant to specific tasks, resulting in the learning of more discriminative node embeddings. Multi-modal Hypergraph Neural Network (MHNet) [106] uses hypergraph structures to model high-order and multi-modal data correlations effectively. It accomplishes this by employing a polynomial hypergraph filter that dynamically extracts multi-scale node features through parametric polynomial fitting.

Recent advancements have been made in convolution operations for point clouds. However, conventional approaches impose a fixed view by using fixed neighborhood sizes for convolution operations on the irregular point clouds. To address this issue, DiffConv [98] introduced density-dilated neighborhoods, where the radius for each point depends on its kernel density. DiffConv also employs masked attention, which introduces task-specific irregularity to the neighborhood, making the convolution process more flexible and effective. Another approach, DeltaConv. [166], proposed a new way to construct anisotropic convolution layers for geometric CNNs. It designed a graph-based anisotropic convolutional operator by combining a set of geometric operators defined on scalar and vector fields to encode directional information for each surface point.

Graph Transformer-based Methods While transformers have previously been used in computer vision, graph-based transformers are explicitly tailored for 3D point cloud representation learning. The transformer architecture is well-suited for point cloud analysis due to its self-attention operator, which functions as a set operator by preserving permutation and cardinality invariance of

input elements [209]. As an example within this category, Point Transformer (PT)[209] introduces a transformer layer that is highly expressive and specifically designed for point cloud processing. The Point Transformer employs local self-attention that ensures scalability even in large scenes. Additionally, integrating vector attention is pivotal in achieving elevated accuracy levels. Another tailored transformer for point clouds is Point cloud transformer (PCT) [42]. PCT innovatively employs a coordinate-based input embedding module to learn distinctive features by combining raw positional encoding and input embedding, harnessing the individual spatial coordinates of each point. Furthermore, it enhances performance by substituting the original self-attention module with an offset-attention module. Unlike PT, PCT excels in capturing global interaction and local neighborhood information.

In order to improve efficiency in point cloud classification, 3D Convolution-Transformer Network (3DCTN) [107] combines convolutions with transformers. Integrating GNN and Transformer approaches helps effectively learn local and global features. To achieve this, 3DCTN utilizes a multi-scale local feature aggregating block and a global feature learning block, implemented by GNNs and Transformers, to process downsampled point sets. While most Transformer-based methods rely on global attention mechanisms to extract point cloud features, they often fail to capture local neighbor-based feature learning. Graph Transformer Network (GTNet) [218] addresses this by using Local and Global Transformer modules. The Local Transformer module calculates neighboring point weights through dynamic graph-based intra-domain cross-attention, assigning different weights to each neighboring point's influence on the centroid's features. In contrast, the Global Transformer module expands the Local Transformer's reach by utilizing global self-attention to enable broader feature extraction.

4.2.2 Trajectory Prediction

Predicting trajectories is a critical task in autonomous vehicle systems, involving the anticipation of future paths for road users based on their past trajectories and the surrounding environment, which includes both static factors like terrain and obstacles, as well as dynamic factors like the movements of nearby agents [58]. Road users include vehicles, cyclists, and pedestrians. While methods utilizing RNNs and CNNs have shown significant success in extracting features from Euclidean spatial data for trajectory prediction, many real-world scenarios involve data generated from non-Euclidean spaces. In such cases, objects can be viewed as nodes forming a graph, with each node connected to others through edges. Utilizing GNNs becomes a natural choice for addressing vehicle trajectory prediction challenges based on interaction-related factors. [60]

Several models have been developed to improve trajectory prediction by adopting the paradigm of spatial and temporal convolution through GNNs. One of them is GRIP [92], which enhances trajectory prediction by incorporating interactions among adjacent objects represented as an undirected graph. It utilizes a GCN module to model the graph network, and the output of GCN is then input into an LSTM encoder-decoder for predicting the trajectories of surrounding vehicles. Another model is SCALE-Net [65], which aims to create an efficient and scalable framework, maintaining high prediction performance for numerous vehicles. It employs an Edge-Enhanced Graph Convolutional Network (EGCN) to update node features based on an attention mechanism influenced by edge features from neighboring nodes. Social-STGCNN [115] represents pedestrian trajectories as spatio-temporal graphs and employs GCN and TCN to operate on these graphs, enabling the model to predict the entire sequence simultaneously. Chandra et al. [20] uses a two-layer Graph-LSTM architecture for trajectory prediction. The initial layer is applied to forecast the future trajectories of traffic participants. In contrast, using a weighted dynamic geometric graph network (DGG), the second layer captures interaction-related factors among participants. The paper also introduces a regularization algorithm based on spectral clustering to minimize the

Table 3. A Comprehensive Overview of Most Related Studies for Traffic Signal Control

Model	Article	Year	Datasets	Simulator	Temporal Module	Spatial Module	Attention Based	Summary
AFMRL	[111]	2023	Simulated and real-world data (Jinan, Hangzhou, Manhattan)	CityFlow	-	GNN	✗	A multi-agent reinforcement learning approach for multi-intersection TSC. Adaptive partitioning is emphasized and feudal hierarchy is explored.
KeyLight	[100]	2023	Simulated and real-world data (Jinan, Hangzhou, New York)	CityFlow	-	GAT	✓	KeyLight integrates reinforcement learning and GNNs. NOVL-LADLE state representation and residual connections are used in the model.
HG-M2I	[179]	2023	real world data (Chengdu)	SUMO	GRU	Bi-GRU	✓	The HG-M2I algorithm, spatial-temporal analysis and multi-agent RL based, optimizes TSC by hierarchical graph structures and input-output correlation.
MetaSTGAT	[156]	2022	Simulated and real-world data (Jinan, Hangzhou)	CityFlow	LSTM	GAT	✓	MetaSTGAT, meta-learning based, merges GAT and LSTM to address spatial-temporal correlations and dynamic interaction of intersections.
PRGLight	[207]	2022	Simulated and real-world data (Jinan, Hangzhou, New York)	CityFlow	-	GNN	✗	PRCOL uses lane capacity for the RL reward function and GNN modules to help RL decide the light phase and duration by predicting traffic flow.
DynSTGAT	[171]	2021	Simulated and real world data (Jinan, Hangzhou, New York)	CityFlow	TCN, LSTM, STGAT	STGAT	✓	DynSTGAT combines spatial-temporal graph attention networks and temporal convolutional network to enhance adaptive TSC.
IHG-MA	[181]	2021	Simulated and real-world data (Chengdu)	SUMO	Bi-GRU	Bi-GRU	✓	IHG-MA uses inductive heterogeneous GNNs to capture traffic features and a decentralized multi-agent actor-critic framework to optimize TSC.
GraphLight	[193]	2021	Simulated data	SUMO	-	GCNN	✗	GraphLight is a decentralized, graph-based, multi-agent system using actor-critic methods for TSC, distinguishing neighboring intersection impacts.
TSC-GNN	[215]	2021	real world data (Jinan, Hangzhou)	-	-	GAT	✓	TSC-GNN is a graph-based model for TSC utilizing probabilistic neural networks, to manage uncertainties and calculate Q-values.
STMARL	[160]	2020	Simulated and real-world data (Hefei, Hangzhou)	CityFlow	RNN	GNN	✓	STMARL applies spatial-temporal RL for TSC, using graphs, RNNs, GNNs, and deep Q-learning for distributed decision-making.
CoLight	[164]	2019	Simulated and real-world data (Jinan, Hangzhou, New York)	CityFlow	-	GAT	✓	CoLight uses graph attention networks for TSC, and captures spatial-temporal impacts from nearby intersections without indexing

error in long-term predictions. GSTCN [129] uses a GCN to capture spatial interactions and a CNN to handle temporal correlations among neighboring vehicles. The spatial-temporal features are encoded and decoded using a GRU network in their framework.

Recently, the attention mechanism is now widely used for various sequence-based tasks, such as predicting the trajectory of autonomous vehicle systems. Several models have been proposed to achieve accurate predictions. Spatial-Temporal Graph Attention network (STGAT) [59] uses an LSTM encoder to encode trajectories. Then, it employs GAT for attention-weighted interaction information and utilizes an LSTM decoder for trajectory prediction. SCOUT [18] uses GAT to account for dynamic agent interactions. Its goal is to enhance socially aware and consistent trajectory predictions. Attention-based Spatio-Temporal Graph Neural Network (AST-GNN) [216] uses a dual-attention mechanism, where the first attention mechanism captures spatial interactions among all agents while the second considers the temporal movement patterns of each agent in the past. Spatio-Temporal Graph Dual-Attention Network (STG-DAT) [88] also employs a dual-attention mechanism to learn representations on spatio-temporal dynamic graphs. It considers historical and future features from state, relation, and scene context information. Triple Policies Fused Hierarchical Graph Networks (Tri-HGNN) [223] proposed triple policies fused hierarchical GNN for pedestrian trajectory prediction. Specifically, the extrinsic-level policy uses GAT for spatial and temporal embeddings, the intrinsic-level policy captures human intention with GCN, and the basic-level policy combines information for predictions through TCN. Heterogeneous Driving Graph Transformer (HDGT) [67] models the driving scene as a heterogeneous graph, considering agents, lanes, and traffic signs as different types of nodes and edges. The transformer structure is applied hierarchically to accommodate the heterogeneous inputs.

4.3 Traffic Signal Control

Traffic signal control (TSC) is an essential aspect of traffic management systems and is an effective measure to alleviate urban traffic congestion, reduce vehicle emissions, and so on. Currently, traffic signal control methods can be divided into three types: predefined fixed-time control, actuated control, and adaptive traffic control. With the rapid increase in the number of vehicles in the city, both the fixed-time control and actuated control methods are hardly effective as they are either short-sighted or rigid without adapting to dynamic traffic demand [160]. Therefore, adaptive traffic signal control (ATSC) has become increasingly popular. However, implicit interactions between intersections and ever-changing traffic conditions make the real-world network of intersections extremely complex, which poses a significant challenge for adaptive traffic signal control.

Multi-agent Reinforcement Learning and Graph Neural Networks. Adaptive traffic signal control systems have benefited greatly from reinforcement learning, which can learn optimal and

complex action policies for the Markov decision process through real-world interaction. [46, 179]. Single-agent reinforcement learning methods are limited to controlling traffic signals in one intersection, as using a global single model for all intersections leads to the curse of dimensionality. Therefore, single-agent RL is commonly restricted to a single isolated intersection without coordination with the neighboring intersections [127]. In order to perform well in multiple intersections, the interaction between intersections must be handled. The most intuitive and practical method to obtain the neighborhood intersection information is by concatenating the state of intersections and their neighbors [63]. However, this approach becomes difficult to extend as the model struggles to converge with increasing dimensionality of inputs. The most popular method nowadays combines robust deep neural networks and multi-agent reinforcement learning, which controls each signal with an RL agent and creates policies for every intersection, making promising progress. More specifically, GNNs can handle graph-structured data in traffic networks, obtaining neighboring intersections information and extending interactions between intersections to non-Euclidean space, which handles spatial dependency in TSC. Moreover, these methods have shown promising progress [26, 45, 171, 193, 207].

Nishi et al. [118] are among the ones who first combine multi-agent reinforcement learning and graph neural networks to address the multi-intersection interaction problem and the spatial dependency. Their work employs GCNs to extract the geometric features. Zhong et al. [215] proposed a model named TSC-GNN to handle a problem that most studies model traffic state deterministically and to exploit the uncertainties of traffic conditions. Yoon et al. [187] claimed that the RL method encountered a restricted exploration problem, which means it cannot handle unseen conditions. They proposed a novel approach to obtain a transferable policy by using graph representation for the state and training it by GNNs. Based on Multi-Agent Reinforcement Learning (MARL), Saki et al. [124] used multi-objective reinforcement learning (MORL) to further improve the performance by determining the policy corresponding to each traffic flow ratio, which achieved the shorted average travel times in all environments compared with ruled based and single objective reinforcement learning. Some more similar literature [100, 112, 171, 179, 181, 193, 207] based on GNNs and reinforcement learning is listed in table 3 .

Attention Mechanism for Multi Intersections. There is a hidden problem related to the impact of traffic signals at neighboring intersections on the target intersection. For instance, the intersections on the main traffic road may have a more significant effect on the target intersection than those on the side road. However, most existing research does not differentiate the impact of surrounding intersections on the target intersection [118, 191]. To address this issue, researchers have applied attention mechanisms to adaptive signal light control. CoLight [164] was the first to use the GAT to distinguish the impact of neighboring intersections and exploit the joint intersections effectively. It created an index-free model of neighboring intersections and averaged the influences of all neighboring intersections with learned attention parameters. However, Sun et al. [100] observed that the attention mechanism may reduce the convergence rate and limit the performance. To address this issue, they proposed NOV-LADLE to maintain a concise state and focus on essential intersections. Besides, they added a residual connection structure to GAT to speed up the convergence rate and improve performance based on the previous work of CoLight. [164]. Other works such as DynSTGAT and TSC-GNN [171, 215] also considered using the graph attention mechanism to solve this problem. Table 3 provides a summary of these works.

Spatial and Temporal Dependency. Moreover, it is essential to consider the historical states of surrounding intersections when predicting the future signal of a target intersection, which creates a temporal dependency among multiple intersection traffic signals. Wang et al. [160] are among the first ones to study the spatio-temporal dependency among multiple traffic signals. It uses graph structures to capture the spatial features and then uses recurrent neural networks to

integrate the historical traffic data. They made decisions for each traffic signal using the deep Q-learning method. Similarly, Li et al. [91] proposed a model that used LSTM and GCN to extract spatial-temporal traffic features of the network of intersections. They used LSTM to process variable-length inputs and extract valid features from historical data and GCN to handle the output of LSTM, which links the interactions of intersections. However, they used imitation learning instead of reinforcement learning. To produce optimal final embeddings of traffic networks, Yang [179] proposed the Hierarchical Graph Multi-agent Mutual Information (HG-M2I) algorithm. It fuses multi-granularity information, i.e., each agent's current and historical step-states, to develop optimal TSC policies. It also measures the correlation between input step-states and output embeddings by maximizing mutual information. Although many studies have tried to incorporate the temporal and spatial influences of the surrounding intersections into the target intersection, they usually consider and use spatial-temporal information separately. Wu et al. [171] proposed DynSTGAT, which employs the TCN to capture the historical and current spatial-temporal information simultaneously. Furthermore, in order to cope with dynamically changing traffic roads, Wang et al. [156] have proposed a meta-learning model named MetaSTGAT based on a GATs that can adapt to the dynamic traffic flow and take full advantage of the spatial-temporal characteristics of multi-intersections. Other literature also considers exploiting spatial and temporal information [156, 181].

Last but not least, some literature [124, 194] claimed that artificially specified action state space may not be able to find an optimal solution under inexperienced traffic situation. Therefore some of the current work take some new approaches to address these problems, such as transfer learning or using inexperienced action space [113, 187].

4.4 Transportation Safety

With the rise of urbanization, traffic accidents have become a significant threat to public health and development. Accurately predicting the likelihood of a traffic accident occurring in a particular area enables safer route planning and efficient emergency response, reducing injuries and property losses. This section provides a comprehensive review of the current studies that explore transportation network safety analysis by utilizing graph neural networks for accident prediction.

Zero-inflated Problems. The most significant difficulty is obtaining spatio-temporal finer-grained and multi-granularity accident forecasting. Due to the rare nature of accidents, more accurate prediction often means a coarser region and time granularity. Therefore, zero-inflated problems arise when spatio-temporal resolution increases in prediction tasks [11], and rare non-zero items in training data disable models to take effects [152].

According to [162], the existing research mainly handles this sparsity problem by predicting accidents within a coarse-grained granularity. There have already been some works to address the imbalanced anomaly data issues [157, 162, 189, 219, 220]. Furthermore, there are mainly two methods: handling the loss function and data preprocessing [61]. More specifically, handling the loss function often means adapting a weighted loss function [61, 151]. While data preprocessing has a broader range of meanings, such as priori knowledge-based data enhancement [219, 220], negative sample undersampling method [189], graph augmentation [157].

Wang et al. [157] used graph augmentation and contrastive loss to improve latent representations in training and proposed an enhanced contrastive GNN-based learning framework to tackle traffic anomaly analysis in ITS. Yu et al. [189] used the negative sample undersampling method to address this problem. They balanced data by matching the number of non-accident (negative) samples with accident (positive) samples and using spatial-temporal GNNs to extract external features for more accurate predictions. Wang et al. [162] exploited the potential chain-like triggering mechanism to connect accident occurrences. They used Spatial-Temporal Categorical GNNs (STC-GNN) to handle the multi-dimensional and chain effect to perform temporal fine-grained accident prediction.

Table 4. A Comprehensive Overview of Most Related Studies for Transportation Safety

Model	Article	Year	Datasets	Spatial Granularity	Temporal Granularity	Solution of zero-inflated	Summary
MSGNN	[143]	2023	loop detectors, GPS probe data (Brisbane, Gold Coast)	Region Level	Short-Term (1h)	clustering-based data imputation	MSGNN, as a sub-area level accident prediction model, captures spatio and temporal relations and uses a data imputation approach for sparse datasets.
TAP	[105]	2023	Real world dataset	Region Level	Short-Term (30min)	-	Multi-task learning framework (TAP) predicts traffic accidents using Spatio-temporal Variational Graph Auto-Encoders, accelerated by edge computing
GGCMT	[61]	2022	Real world dataset (NYC)	Region Level	Mid-Term (3h)	prior risk data enhancement method.	Computer-vision-based GGCMT predicts accidents using a gated graph convolutional multi-task model, improved with prior risk data enhancement methods.
DSTGCN	[189]	2021	Real world dataset	Link Level	Short-Term	Negative sample undersampling method	DSTGCN predicts traffic accidents from heterogeneous data, capturing spatio-temporal correlations by Deep Spatio-Temporal Graph Convolutional Network.
GSNet	[131]	2021	Real world dataset (NYC, Chicago)	Region Level	Short-term(1h)	Weight loss function	GSNet predicts traffic accidents by analyzing spatio-temporal and heterogeneous data, using a specialized loss function for rare events.
GraphCast	[204]	2020	Real world dataset (NYC)	Region Level	Long-term (7day)	-	GraphCast, a multi-modal graph neural network, forecasts fine-grained traffic risks in cities by combining social media and remote sensing data.
RiskSeq	[220]	2020	Real world dataset (NYC, Suzhou)	Region Level	Short-term (10min)	priori knowledge-based data enhancement	RiskSeq, a fine-grained and multi-step accident prediction model, combines Differential Time-varying GCN and hierarchical sequence learning.
RiskOracle	[219]	2020	Real world dataset (NYC, Suzhou)	Region Level	Short-term (30min)	priori knowledge-based data enhancement	RiskOracle, a minute-level accident prediction model, combines Differential Time-varying Graph network, multi-task and region selection strategies.
TA-STAN	[222]	2019	Real world dataset (NYC)	Region Level	Mid-Term (12h)	-	TA-STAN predicts accidents by analyzing real-world traffic data, vehicle types, and external factors with a Spatial-Temporal Attention Network.

Spatial and Temporal Granularity. In the field of transportation safety, prediction models can be classified into four categories based on their temporal and spatial granularity. One the one hand, the duration of prediction periods divides models into two types: long-term (day-level prediction) [55, 192, 204] and mid-term (hour-level prediction) [11, 22, 61, 121, 219]. On the other hand, the size of the prediction region distinguishes models into two categories: link level [189, 222] and region level [143, 151, 162].

Zhou et al. [219] introduced a three-stage RiskOracle framework for minute-level citywide traffic accident prediction, which utilizes a Multi-task Differential Time-varying Graph convolution Network (Multi-task DTGN) to model dynamic subregion-wise correlations. It incorporates a cosensing strategy for data preprocessing to infer traffic status and tackles zero-inflation issues with a priori knowledge-based data enhancement. Zhang et al. [204] first proposed a multi-modal sensing and GNN-based approach called GraphCast, which can be used to predict accidents at the regional level. This approach uses social media and remote sensing data to address the challenges of noisy and heterogeneous multi-modal data. Tran et al. [143] introduced a new model for predicting traffic incidents across an entire network rather than just at the level of individual links. They achieve this using a Multi-structured Graph Neural Network (MSGNN) to extract area-wide features from various data sources rather than link-level synchronization and map-matching. This approach makes incident prediction faster and more efficient. However, as previously discussed, the issue of zero-inflation arises as the spatial resolution becomes more refined, which makes model training and prediction difficult. Huang et al. [54] have also pointed out that many machine-learning techniques predict the number of traffic accidents in each cell of a discretized grid without considering the underlying graph structure of road networks. Furthermore, accurate prediction at the link-level requires a complex fusion of heterogeneous data resources, necessitating "map-matching" to represent all the data with different granularity in the same map system.

Spatial-temporal Correlation. Predicting traffic accidents can be challenging, as traffic accidents are sparse and have complex causes. We need to consider the spatial and temporal traffic features to make better predictions. Some articles [189, 192] have pointed out that existing methods either ignore spatial-temporal correlations or make predictions at a coarse-grained level without considering the underlying graph structure of road networks. Zhou et al.[220] proposed a deep neural network approach named RiskSeq that uniquely addresses sporadic events with a self-adaptive ranking method. It uses a Differential Time-varying Graph Convolution Network (DT-GCN) enhanced with node-wise proximity and signal-wise differential operations to capture dynamic traffic and accident correlations. The framework also features a Context-Guided LSTM to decode risks across multiple spatial scales. Zhou claims that their work is the first to focus on spatiotemporal multi-granularity urban traffic risk prediction, transforming the prediction of sporadic events into a task involving learnable self-adaptive ranking. Yu et al. [189] addressed the link-level accident prediction problem by proposing a framework based on a spatio-temporal convolutional network.

Their model predicts link-level incident risk by learning spatial-temporal features from a graph of road networks. They utilized the graph convolutional operation to capture the dynamic variations in both spatial and temporal perspectives. Liu et al. [105] proposed a multi-task learning framework (TAP) based on edge computing, which uses spatio-temporal variational graph auto-encoders to enhance traffic accident prediction accuracy by analyzing dynamic spatial-temporal traffic data correlations and integrating external factors. Wang et al. [151] introduced a region-wide accident prediction model called GSNet, which captures the geographical and semantic spatial-temporal correlations. The model also features a weighted loss function to tackle the zero-inflation issue. The table 4 lists some other spatial-temporal models [203, 222].

4.5 Demand Prediction

The growth of modern cities has caused an increase in traffic-related issues, which has put a lot of pressure on public transportation systems. To tackle this problem, ride-hailing services such as Uber, Lyft, and DiDi, as well as bike-sharing services like MoBike have emerged as potential solutions [140, 224]. As a result, there is now a pressing need for accurate traffic demand prediction systems that can forecast future crowd demands with precision [141]. The main goal of these prediction models is to anticipate the number of users who will require transportation to or from specific areas or locations. These predictions are essential for scheduling future transportation services and other downstream tasks.

Deep learning methods have shown great potential in handling data within Euclidean spaces. However, the real-world urban traffic data usually exhibit non-Euclidean structures that require specific approaches. For example, a city's spatial distribution of bike-sharing stations doesn't follow a grid-like data structure. In such cases, graph-structured data is better for preferable traffic demand prediction tasks, as it can finely capture the non-Euclidean relationships among nodes.

Traffic Zone-based Graph Methods. To depict the dynamic traffic systems with graph structures, a straightforward and effective approach is to model the connectivity between zones of cities. One of the pioneering works in utilizing graph learning methods for demand prediction tasks is Spatio-Temporal Multi-Graph Convolution Network (ST-MGCN) [38]. It proposes to exploit graph structures from multiple perspectives to capture comprehensive information on the spatio-temporal characteristics of traffic systems. Specifically, ST-MGCN builds the graphs of zones from three angles: a neighborhood graph based on the spatial proximity, a functionality graph defined by the POI similarity, and a transportation connectivity graph induced by road networks such as motorways, highways, or public transportation systems like subways. A multi-graph convolution is then introduced to model the spatial dependencies between regions and provide informative representations for downstream demand prediction tasks. Similarly, PGDRT [82] builds the zone-wise relational graph using three types of temporal characteristics: adjacent visual characteristics, periodic characteristics, and representative characteristics, to provide a more comprehensive view of temporal features in traffic systems. To fully exploit the rich information from multiple traffic systems, Multiview Spatio-Temporal Graph Neural Networks (MSTGNN) [211] proposes a multi-view graph that jointly depicts the demand relationship between bus, metro, and taxi demands. The multiview graph enables MSTGNN to capture the interaction dependencies among the travel demands of different transportation systems. An auxiliary loss is used to encourage the consistency between graph features from multiple views and enhance the performance of TGCN modules.

Spatio-temporal Graph-based Methods Classical GNN models for traffic demand prediction treat the spatial dependency as a static graph and cannot depict dynamic features. However, in reality, the spatial dependencies between most nodes change over time, while others remain relatively constant. To address this limitation, the Dynamical Spatio-Temporal Graph Neural Network (DSTGNN) was introduced in a recent study [56]. This model evaluates the stability

Table 5. A Comprehensive Overview of Most Related Studies for Demand Prediction

Model	Article	Year	Prediction Task	Graph Views	GNN Module	Temporal Module	Summary
PGDRT	[82]	2023	Taxi Passenger	Neighborhood, Function, Connectivity	GCN	ConvLSTM	PGDRT considers a region's unique characteristics and the influence of regions on the model of the dependent relationship between regions.
MSTGNN	[211]	2023	Bus, Metro, Taxi	Neighborhood, Connectivity	GCN	Temporal GCN	MSTGNN uses a multiview graph consisting of bus, metro, and taxi views, with each view containing both local and global graphs.
STGMT	[165]	2023	Taxi & Highway	Traffic Network	Node2Vec	Multi-head Attention	STGMT combines Multi-head Temporal Attention (MTA) and Multi-head Temporal Interactive Attention (MTIA) for temporal features.
PAG-TSN	[87]	2023	Ride-hailing	Distance, POI relation	BAT-GCN	PA-GRU	PAG-TSN uses a bicomponent attention GCN and a periodic attentional GRU to integrate the extracted spatio-temporal information.
HetGNN-LSTM	[117]	2023	Taxi	Decentralized taxi graph	HetGNN	LSTM	HetGNN-LSTM proposes a semi-decentralized approach utilizing multiple cloudlets, moderately sized storage, and computation devices.
MFGCN	[97]	2023	Ride-hailing	OD network	MODGCN	TAS-LSTM	MFGCN is a multimodal fusion GCN that consists of a multimodal module to incorporate weather and temporal activity patterns.
SGCNPM	[182]	2023	Dockless Bike-Sharing	Distance, Function, Interconnectio	MGCN	LSTM	SGCNPM considers time, built environment, and weather to create a prediction method considering the influence of multiple factors.
DSTGNN	[56]	2022	Taxi & Bike	Spatial dependency	DCNN	Multi-head Attention	DSTGNN builds spatial graphs based on the stability of the node's spatial dependence to capture the dynamical relationship.
DMVST-VGNN	[72]	2022	Ride-hailing	Multi-view Graph Generation	GAT	Multi-head Attention	The Model integrates 1D CNN, Multi-Graph Attention Neural Networks, and Transformer to construct multiview spatio-temporal information.
ST-MGCN	[38]	2019	Ride-hailing	Neighborhood, Function, Connectivity	ChebNet	RNN	ST-MGCN uses GNNs to model non-Euclidean pair-wise correlations between different regions by designing a spatio-temporal multi-graph.

of a node's spatial dependence based on the number of dissimilar neighbors and constructs a spatio-temporal graph that evolves over time. To encode the spatio-temporal information, the model uses a spatio-temporal embedding network that combines a Diffusion Convolution Neural Network (DCNN) with a modified transformer.

Dynamic Graph-based Methods. The traditional approach to modeling cities is to divide them into grid-like zones and construct graphs based on these divisions. However, this approach can lead to suboptimal solutions, and adapting to dynamic graph structures remains challenging. A new solution called Deep Multi-View Spatio-temporal Virtual Graph Neural Network (DMVST-VGNN) [72] improves learning capabilities related to spatial dynamics and long-term temporal dependencies. The DMVST-VGNN method proposes a graph generation process that provides a more flexible and fine-grained perspective on the spatio-temporal relationships between regions, as opposed to the simplistic grid-based division of the map. Another proposal by Nazzal et al. [117] extends the idea of dynamic and flexible graph structures to decentralized edge-computing scenarios and introduces a heterogeneous GNN-LSTM algorithm. This algorithm is designed to handle dynamic taxi graphs where taxis serve as nodes. The proposed heterogeneous GNN-LSTM structure has demonstrated the ability to capture dynamic decentralized graph structures and has shown promising results in taxi-level demand and supply forecasting.

Improvements on Graph Encoders. The traditional graph convolution network has limited capability to represent the complex information in traffic zone graphs. However, some works aim to enhance the expressiveness of graph encoders. STGMT [165] proposes the Sandwich-Transformer for processing spatio-temporal traffic graphs, which is composed of a Multi-head Temporal Attention (MTA) and a Multi-head Temporal Interactive Attention (MTIA). PAG-TSN [87] constructs a Bicomponent Attention Graph Convolution model (BAT-GCN) and a periodic attentional gated recurrent unit model to capture geographical relationships and temporal features of different periods, respectively. While previous research primarily concentrates on processing plain time-series traffic demand data for predictions, it is essential to recognize that contextual information and multimodal attributes, such as weather conditions, significantly impact ride-hailing and other public traffic systems. To tackle these challenges, Multimodal Fusion Graph Convolutional Network (MFGCN) [97] introduces an innovative Multimodal Fusion Graph Convolutional Network for traffic demand prediction. MFGCN incorporates a Multimodal Origin-Destination GCN (MODGCN) that comprises three GCNs to capture spatial patterns and a Multimodal Attribute Enhancement (MAE) module for integrating dynamic weather and metadata. SGCNPM [182] utilizes multiple modules that consist of GCN and LSTM operators to model the multiple factors in a dynamic traffic system, including time periods, built environment, and weather, to predict the short-term demand of a dockless bike-sharing system.

A comprehensive overview of most related studies for demand prediction can be found in table 5.

4.6 Parking Management

The issue of parking in large cities has become a significant concern due to the limited number of on-street parking slots and the increasing traffic. To address this issue, an intelligent parking management system is required. A widely studied research field is parking availability prediction, which involves reliably predicting future parking occupancies. The ability to predict parking availability on a city-wide scale is essential for the successful development of Parking Guidance and Information (PGI) systems, such as Baidu Map [122] and Google Map [4], making it an important research aspect in ITS field.

Predicting the availability of parking spaces is a complex task that poses several challenges, such as the non-Euclidean spatial autocorrelation between parking lots, the dynamic temporal autocorrelation within and between parking lots, and the lack of real-time data obtained from sensors to determine parking availability. To address the challenges mentioned above, graph neural networks and graph-structured data have been identified as a natural solution to process the spatial-temporal structures and predict parking availability. Although there have been early attempts to replicate the success of GCN and LSTM structures in such spatio-temporal prediction tasks [180], more work is needed to design specific frameworks that can better incorporate the characteristics of parking availability prediction into model structures.

As one of the pioneering works on modeling the parking availability prediction with graph-based models, SHARE [201] and its variant SHARE-X [202] proposes a Semi-supervised Hierarchical Recurrent Graph Neural Network to analyze spatio-temporal parking data. Specifically, SHARE proposes a hierarchical graph convolution module that captures non-Euclidean spatial correlations between parking lots. It consists of two blocks: a contextual graph convolution block for local spatial dependencies and a soft clustering graph convolution block for global spatial dependencies. SHARE-X extends the idea of SHARE to address the lack of real-time sensors in real-world scenarios. Particularly, It leverages a parking availability approximation module to estimate parking availability for parking lots without sensor monitoring.

To better depict the strong spatiotemporal contextual autocorrelation between vacant parking spaces, dConvLSTM-DCN [35] analyzed the historical zone-wise parking space data and found that there is both a temporal correlation within each parking lot and a spatial correlation among different parking spaces. Based on this observation, the study proposed a deep learning framework called dConvLSTM-DCN (dual Convolutional Long Short-Term Memory with Dense Convolutional Network) to predict the availability of vacant parking places in the short-term (within 30 minutes) and long-term (over 30 minutes) zone-wisely. The framework consists of two parallel ConvLSTM components that capture the spatial correlations among parking lots and provide an informative representation of the prediction process.

The traditional methods of obtaining real-time on-street parking occupancy information rely on deploying many sensors. However, the high costs of existing parking availability prediction models have limited their large-scale applications in more cities and areas. To address this challenge of limited information, MePark [208] aims to predict real-time on-street parking availability across a city using pre-existing infrastructure and easily accessible data without relying solely on specially deployed sensors. Specifically, MePark utilizes an iterative mechanism to effectively combine the aggregated inflow and individual parking duration predictions to exploit the transaction data adequately. Additionally, it extracts discriminative features from multiple data sources, combining the MGCN and the LSTM network to capture complex spatio-temporal correlations.

5 Challenges and Future Directions

After thoroughly analyzing the current studies on GNNs in ITS, we discuss the challenges and future directions for applying GNNs to ITS. This is important to identify any gaps that need to be addressed and to provide insights for further research.

5.1 Research Challenges

5.1.1 Data

Constructing datasets is one of the main challenges when using models for transportation systems. However, data privacy is a significant concern when collecting information from traffic sensors or GPS data. Currently, there are only a few publicly available data sources, such as Data.gov, The University of Sydney Intelligent Vehicles and Safety Systems, and Connected Vehicle DataSets from the Safety Pilot Model Deployment [39]. Some researchers [32, 97, 106, 154] have experimented with multi-modal models to obtain data from richer sources, such as social media, but there are issues related to credibility and a lack of valuable information. As a result, generating a large, high-quality, and comprehensive dataset in ITS remains a formidable task.

5.1.2 Model

Domain-specific Model Design. Intelligent Transportation system is a complex data network encompassing various nodes and edges such as roads, intersections, and vehicles. However, designing GNN models that can efficiently learn from such a heterogeneous and complex structure requires much effort. The design of GNN applications in ITS heavily depends on the specific goals of the corresponding applications, as different goals require using different graph models and construction techniques. For instance, GNNs are commonly used in traffic forecasting and travel demand modeling to predict features or variables over graph nodes. While in areas such as traffic signal control, GNNs focus on learning control policies or unraveling agent interactions that involve learning or predicting over edges or the entire graph. Besides, GNNs face different challenges in various transportation domains. The pure GNN models can not effectively solve the problem, so some scholars have explored the potential of combining GNNs with other approaches. For instance, in decision-making problems, such as traffic signal control, reinforcement learning is an effective technique. When multiple intersections interact, multi-agent reinforcement learning methods combined with GNNs have been proposed [118, 193, 193]. In some particular scenarios, such as traffic accident prediction, positive samples like accidents can be rare when predicting within a fine-grained granularity. To improve accuracy, we can use data augmentation techniques like a priori knowledge-based data enhancement [219, 220] and negative sample undersampling methods [189]. Nearly every transportation domain has its own domain-specific problems and unique characteristics. Therefore, combining GNNs and other techniques requires nuanced graph construction, tailored problem analysis, and painstaking design.

Dynamic Spatio-temporal Dependency. Modeling spatio-temporal dependencies in ITS using graph neural networks is challenging. This is because it involves effectively capturing the dynamic and complex spatial interactions within the transportation network, as well as the temporal dynamics that are inherent to the ever-changing nature of traffic patterns. Transportation networks often have dynamic spatial dependencies, meaning the graph structure can change over time due to the constantly changing urban environment. For instance, in the field of trajectory prediction, it is essential to identify significant agents and objects, such as vehicles, cyclists, and pedestrians, that can impact the trajectory of the prediction. Therefore, a graph framework that can adapt to these changes in real time is required to ensure prediction accuracy. Meanwhile, regarding temporal dependency, traffic conditions at a given time are influenced by numerous past events. Accurately capturing these long-term dependencies is essential for accurate forecasting, but it

can be computationally challenging and requires advanced memory mechanisms in the model. Additionally, real-time data processing is essential for practical ITS applications, further intensifying the challenge. The model must integrate and process this multifaceted data and evolve and adapt in an environment characterized by constant change and uncertainty. Therefore, modeling spatio-temporal dependencies is a pivotal yet challenging aspect of leveraging GNNs in ITS.

Robustness, Reliability, Interpretability. Deep learning has received criticism for its non-interpretable and black-box working system. This means it can be challenging to determine the rationality of a feasible scenario suggested by a graph-based deep learning approach in transportation safety or other related fields, especially given the high opportunity costs. Moreover, it is crucial to ensure that neural network methods can continue to work reliably in larger-scale real-world scenarios, even during rush hours, sensor failure, or hacking. Therefore, while we work to improve model performance, we must also remain aware of potential failures and undetected anomalies. Lastly, scalability is a critical factor that needs to be considered. However, current GNN frameworks based on TensorFlow, PyTorch, DGL, and PyG all have scalability limitations. This restricts applying GNNs on large-scale graphs due to a lack of system support [94].

5.1.3 Computation

Processing, storing, and transmitting large amounts of data has become increasingly important in today's world of big data, particularly in the field of ITS. GNNs and deep learning techniques are widely used in ITS, but they face significant challenges due to their high computational needs. These challenges become even more difficult to tackle when dealing with real-time or near-real-time inference and processing large amounts of data from extensive camera networks. Moreover, the limited resources of IoT devices, such as restricted memory and computing power, make these challenges more complex. To address these issues, researchers have proposed several solutions, such as edge computing, graph sampling, hardware acceleration, and optimized algorithms.

5.2 Future Directions

More Integration of Advanced Techniques. As mentioned above, GNNs are powerful for capturing spatial-temporal relationships and making inferences on graph data structures. However, different problems necessitate unique model designs due to their distinct characteristics and challenges. Moreover, integrating other techniques into GNN frameworks can enhance model performance and facilitate real-world applications. For instance, employing the edge learning paradigm [197] in GNN frameworks addresses the storage, memory, and computational limitations of data-producing devices. This approach enables distributed edge devices to collaboratively train models and conduct inferences, ensuring privacy and security [197]. Transfer learning [113] and meta-learning [156] can significantly improve model adaptability across cities with varying traffic patterns. In conclusion, the fusion of GNNs with advanced techniques like reinforcement learning, transfer learning, meta-learning, generative adversarial networks (GANs), semi-supervised learning, and Bayesian networks opens new avenues for tackling domain-specific problems and challenges. This synergistic approach yields more robust and versatile solutions and opens up exciting possibilities for solving complex, real-world problems across various domains. As research progresses, it is vital to continue exploring these combinations, constantly pushing the boundaries of what can be achieved with GNNs and their integrations with other technologies.

More Expanding Applications of GNNs. More research is needed to fully utilize the potential of GNNs in ITS. Most of the current work has focused on traffic prediction, although this is indeed a substantial basic research. In addition, graph neural networks still have excellent potential for development, so we need to explore the applications of graph neural networks further. On the one hand, we should further improve the efficiency, robustness, and generality of GNN models. One

way to achieve this is to enable multi-modal learning [106, 185], which allows the model to access a richer set of contextual information. Additionally, we can use more complex graph structures such as heterogeneous graphs [117] and hypergraphs [178] and handle larger graph structures. On the other hand, we can also apply GNNs to other domains within ITS. Taking 3D structure understanding of autonomous vehicles as a detailed example, traditional transformer architectures [42, 209] in point cloud processing are often less efficient. However, by exploring the combination of graph convolution and self-attention, we can improve feature extraction and effectively capture local and global contexts [107]. While we have covered several domains, from traffic prediction to traffic safety, there are still more domains to explore, such as route planning, urban land-use planning, and traffic pattern recognition. Further investigating the application of GNNs in more ITS domains can bring new insights and opportunities for its performance in more general domains.

More Comprehensive Experiments. Currently, some research experiments in the field of ITS rely on simulators. However, the data generated by traffic simulation software may not accurately fit real-world situations due to various factors such as differences in drivers' behaviors and alternative route planning [194]. Additionally, it is important to recognize that even when models are tested with real-world data, the testing may only be conducted on a small scale, or the running time of the model may not be reported. These limitations do not guarantee the model's reliability, robustness, and the ability to generalize to real-world situations. According to Shi et al., [130], some models, like DQNs-based RL, suffer from performance degradation while dealing with large-scale road networks or missing data, making it challenging to generalize. Therefore, it is crucial to develop more comprehensive experiments with large-scale real-world data to evaluate models.

6 Conclusion

With the rapid development of deep learning, graph neural networks have emerged as a promising tool in the field of intelligent transportation system. However, most of the current research on GNNs in ITS has focused on their use in traffic forecasting while neglecting other critical areas, such as autonomous vehicles and transportation safety. In this work, we have reviewed and analyzed a selection of representative papers from 2018 to 2023 that explore the different applications of GNNs in six domains of ITS. We have summarized and classified these papers based on the research field related, graph methods utilized, and domain-specific challenges encountered, and finally presented informative tables and lists. Our observations show that most studies are limited to specific functionalities of GNNs, such as modeling graph-structure data and capturing spatio-temporal relationships. However, there is still much potential to fully harness the power of GNNs and expand their applications in other areas of ITS. Moreover, we have identified common challenges that need to be addressed when applying GNNs in ITS, including issues related to *data*, *model*, and *computation*. We have also highlighted the future direction of GNNs in ITS, emphasizing the importance of combining them with other techniques, expanding their applications, and conducting more comprehensive experiments.

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References

- [1] Sergi Abadal, Akshay Jain, Robert Guirado, Jorge López-Alonso, and Eduard Alarcón. 2021. Computing graph neural networks: A survey from algorithms to accelerators. *CSUR* 54, 9 (2021).
- [2] Dharyll Prince Mariscal Abellana. 2023. Multivariate Travel Time Forecasting in a Traffic Network Using Fuzzy Cognitive Mapping. In *AIC*.
- [3] Mohammed S Ahmed and Allen R Cook. 1979. *Analysis of freeway traffic time-series data by using Box-Jenkins techniques*. Number 722.
- [4] Neha Arora, James Cook, Ravi Kumar, Ivan Kuznetsov, Yechen Li, Huai-Jen Liang, Andrew Miller, Andrew Tomkins, Iveel Tsogsuren, and Yi Wang. 2019. Hard to park? Estimating parking difficulty at scale. In *KDD*.
- [5] Ashley Auer, Shelley Feese, Stephen Lockwood, and Booz Allen Hamilton. 2016. *History of intelligent transportation systems*. Technical Report.
- [6] Lei Bai, Lina Yao, Salil S. Kanhere, Xianzhi Wang, and Quan Z. Sheng. 2019. STG2Seq: Spatial-Temporal Graph to Sequence Model for Multi-step Passenger Demand Forecasting. In *IJCAI*.
- [7] Lei Bai, Lina Yao, Can Li, Xianzhi Wang, and Can Wang. 2020. Adaptive graph convolutional recurrent network for traffic forecasting. In *NeurIPS*.
- [8] Song Bai, Feihu Zhang, and Philip HS Torr. 2021. Hypergraph convolution and hypergraph attention. *Pattern Recognition* 110 (2021).
- [9] Muhammet Balcilar, Renton Guillaume, Pierre Héroux, Benoit Gaüzère, Sébastien Adam, and Paul Honeine. 2021. Analyzing the expressive power of graph neural networks in a spectral perspective. In *ICLR*.
- [10] Muhammet Balcilar, Guillaume Renton, Pierre Héroux, Benoit Gauzere, Sébastien Adam, and Paul Honeine. 2020. Bridging the gap between spectral and spatial domains in graph neural networks. *arXiv preprint arXiv:2003.11702* (2020).
- [11] Jie Bao, Pan Liu, and Satish V Ukkusuri. 2019. A spatiotemporal deep learning approach for citywide short-term crash risk prediction with multi-source data. *Accident Analysis & Prevention* 122 (2019).
- [12] Jaume Barceló, Lidin Montero, Laura Marqués, and Carlos Carmona. 2010. Travel time forecasting and dynamic origin-destination estimation for freeways based on bluetooth traffic monitoring. *TRR* 2175, 1 (2010).
- [13] Filippo Maria Bianchi, Daniele Grattarola, Lorenzo Livi, and Cesare Alippi. 2021. Graph neural networks with convolutional arma filters. *TPAMI* 44, 7 (2021).
- [14] George EP Box, Gwilym M Jenkins, Gregory C Reinsel, and Greta M Ljung. 2015. *Time series analysis: forecasting and control*. John Wiley & Sons.
- [15] Shaked Brody, Uri Alon, and Eran Yahav. 2021. How attentive are graph attention networks? *arXiv preprint arXiv:2105.14491* (2021).
- [16] Khac-Hoai Nam Bui, Jiho Cho, and Hongsuk Yi. 2022. Spatial-temporal graph neural network for traffic forecasting: An overview and open research issues. *Applied Intelligence* 52, 3 (2022).
- [17] Robert C Bushnell, James T Low, and James B Wiley. 1981. Transportation Network Models: Past Problems and Prospects for the 1980s. *International Journal of Physical Distribution & Materials Management* 11, 8 (1981).
- [18] Sandra Carrasco, D Fernández Llorca, and MA Sotelo. 2021. Scout: Socially-consistent and understandable graph attention network for trajectory prediction of vehicles and vrus. In *IEEE Intelligent Vehicles Symposium*.
- [19] T-H Hubert Chan and Zhibin Liang. 2020. Generalizing the hypergraph laplacian via a diffusion process with mediators. *TCS* 806 (2020).
- [20] Rohan Chandra, Tianrui Guan, Srujan Panuganti, Trisha Mittal, Uttaran Bhattacharya, Aniket Bera, and Dinesh Manocha. 2020. Forecasting trajectory and behavior of road-agents using spectral clustering in graph-lstms. *IEEE Robotics and Automation Letters* 5, 3 (2020).
- [21] H Chang, Youngjoo Lee, B Yoon, and Sanghoon Baek. 2012. Dynamic near-term traffic flow prediction: system-oriented approach based on past experiences. *IET intelligent transport systems* 6, 3 (2012), 292–305.
- [22] Chao Chen, Xiaoliang Fan, Chuanpan Zheng, Lujing Xiao, Ming Cheng, and Cheng Wang. 2018. Sdcae: Stack denoising convolutional autoencoder model for accident risk prediction via traffic big data. In *CBD*.
- [23] Changlu Chen, Yanbin Liu, Ling Chen, and Chengqi Zhang. 2022. Bidirectional spatial-temporal adaptive transformer for Urban traffic flow forecasting. *TNNLS* (2022).
- [24] Ming Chen, Zhewei Wei, Zengfeng Huang, Bolin Ding, and Yaliang Li. 2020. Simple and deep graph convolutional networks. In *ICML*.
- [25] Kyunghyun Cho, Bart van Merriënboer, Dzmitry Bahdanau, and Yoshua Bengio. 2014. On the Properties of Neural Machine Translation: Encoder-Decoder Approaches. In *SSST@EMNLP*.
- [26] Tianshu Chu, Jie Wang, Lara Codecà, and Zhaojian Li. 2019. Multi-agent deep reinforcement learning for large-scale traffic signal control. *TITS* 21, 3 (2019).
- [27] Fan RK Chung. 1997. *Spectral graph theory*. Vol. 92. American Mathematical Soc.

- [28] Antonio Comi and Antonio Polimeni. 2020. Bus travel time: Experimental evidence and forecasting. *Forecasting* 2, 3 (2020).
- [29] Zhiyong Cui, Kristian Henrickson, Ruimin Ke, and Yin Hai Wang. 2019. Traffic graph convolutional recurrent neural network: A deep learning framework for network-scale traffic learning and forecasting. *TITS* 21, 11 (2019).
- [30] Michaël Defferrard, Xavier Bresson, and Pierre Vandergheynst. 2016. Convolutional neural networks on graphs with fast localized spectral filtering. In *NeurIPS*, Vol. 29.
- [31] Carl Doersch. 2016. Tutorial on variational autoencoders. *arXiv preprint arXiv:1606.05908* (2016).
- [32] Panagiotis Fafoutellis and Eleni I Vlahogianni. 2023. Traffic demand prediction using a social multiplex networks representation on a multimodal and multisource dataset. *IJTST* (2023).
- [33] Xiaochen Fan, Chaocan Xiang, Liangyi Gong, Xin He, Yuben Qu, Saeed Amirgholipour, Yue Xi, Priyadarsi Nanda, and Xiangjian He. 2020. Deep learning for intelligent traffic sensing and prediction: recent advances and future challenges. *CCF Transactions on Pervasive Computing and Interaction* 2 (2020).
- [34] Zheng Fang, Qingqing Long, Guojie Song, and Kunqing Xie. 2021. Spatial-Temporal Graph ODE Networks for Traffic Flow Forecasting. In *KDD*.
- [35] Yajing Feng, Yingying Xu, Qian Hu, Sujatha Krishnamoorthy, and Zhenzhou Tang. 2022. Predicting vacant parking space availability zone-wisely: A hybrid deep learning approach. *Complex & Intelligent Systems* 8, 5 (2022).
- [36] Yifan Feng, Haoxuan You, Zizhao Zhang, Rongrong Ji, and Yue Gao. 2019. Hypergraph neural networks. In *AAAI*.
- [37] Johannes Gasteiger, Aleksandar Bojchevski, and Stephan Günnemann. 2018. Predict then propagate: Graph neural networks meet personalized pagerank. *arXiv preprint arXiv:1810.05997* (2018).
- [38] Xu Geng, Yaguang Li, Leye Wang, Lingyu Zhang, Qiang Yang, Jieping Ye, and Yan Liu. 2019. Spatiotemporal multi-graph convolution network for ride-hailing demand forecasting. In *AAAI*.
- [39] J Guerrero-Ibañez, Juan Contreras-Castillo, and Sherali Zeadally. 2021. Deep learning support for intelligent transportation systems. *Transactions on Emerging Telecommunications Technologies* 32, 3 (2021).
- [40] R Günther, Tobias Wenzel, Mario Wegner, and Rasmus Rettig. 2017. Big data driven dynamic driving cycle development for busses in urban public transportation. *Transportation Research Part D: Transport and Environment* 51 (2017).
- [41] Ge Guo and Wei Yuan. 2020. Short-term traffic speed forecasting based on graph attention temporal convolutional networks. *Neurocomputing* 410 (2020).
- [42] Meng-Hao Guo, Jun-Xiong Cai, Zheng-Ning Liu, Tai-Jiang Mu, Ralph R Martin, and Shi-Min Hu. 2021. Pct: Point cloud transformer. *Computational Visual Media* 7 (2021).
- [43] Shengnan Guo, Youfang Lin, Ning Feng, Chao Song, and Huaiyu Wan. 2019. Attention based spatial-temporal graph convolutional networks for traffic flow forecasting. In *AAAI*.
- [44] Yulan Guo, Hanyun Wang, Qingyong Hu, Hao Liu, Li Liu, and Mohammed Bennamoun. 2020. Deep learning for 3d point clouds: A survey. *TPAMI* 43, 12 (2020).
- [45] Jayesh K Gupta, Maxim Egorov, and Mykel Kochenderfer. 2017. Cooperative multi-agent control using deep reinforcement learning. In *Autonomous Agents and Multiagent Systems: AAMAS Workshops*.
- [46] José A Guzmán, Germán Pizarro, and Felipe Núñez. 2023. A reinforcement learning-based distributed control scheme for cooperative intersection traffic control. *IEEE Access* (2023).
- [47] Arya Ketabchi Haghighat, Varsha Ravichandra-Mouli, Pranamesh Chakraborty, Yasaman Esfandiari, Saeed Arabi, and Anuj Sharma. 2020. Applications of deep learning in intelligent transportation systems. *Journal of Big Data Analytics in Transportation* 2 (2020).
- [48] Will Hamilton, Zitao Ying, and Jure Leskovec. 2017. Inductive representation learning on large graphs. In *NeurIPS*.
- [49] William L Hamilton. 2020. *Graph representation learning*. Morgan & Claypool Publishers.
- [50] Liangzhe Han, Bowen Du, Leilei Sun, Yanjie Fu, Yisheng Lv, and Hui Xiong. 2021. Dynamic and multi-faceted spatio-temporal deep learning for traffic speed forecasting. In *KDD*.
- [51] Dailan He, Yusheng Zhao, Junyu Luo, Tianrui Hui, Shaofei Huang, Aixi Zhang, and Si Liu. 2021. Transrefer3d: Entity-and-relation aware transformer for fine-grained 3d visual grounding. In *Proceedings of the 29th ACM International Conference on Multimedia*.
- [52] Mikael Henaff, Joan Bruna, and Yann LeCun. 2015. Deep convolutional networks on graph-structured data. *arXiv preprint arXiv:1506.05163* (2015).
- [53] Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. *Neural Computation* 9, 8 (1997).
- [54] Baixiang Huang and Bryan Hooi. 2022. Traffic Accident Prediction using Graph Neural Networks: New Datasets and the TRAVEL Model. *Traffic* 27, 29 (2022).
- [55] Chao Huang, Chuxu Zhang, Peng Dai, and Liefeng Bo. 2019. Deep dynamic fusion network for traffic accident forecasting. In *CIKM*.
- [56] Feihu Huang, Peiyu Yi, Jince Wang, Mengshi Li, Jian Peng, and Xi Xiong. 2022. A dynamical spatial-temporal graph neural network for traffic demand prediction. *Information Sciences* 594 (2022).

- [57] Liping Huang, Yongjian Yang, Xuehua Zhao, Chuang Ma, and Hepeng Gao. 2018. Sparse data-based urban road travel speed prediction using probabilistic principal component analysis. *IEEE Access* 6 (2018).
- [58] Renhao Huang, Hao Xue, Maurice Pagnucco, Flora Salim, and Yang Song. 2023. Multimodal trajectory prediction: A survey. *arXiv preprint arXiv:2302.10463* (2023).
- [59] Yingfan Huang, Huikun Bi, Zhaoxin Li, Tianlu Mao, and Zhaoqi Wang. 2019. Stgat: Modeling spatial-temporal interactions for human trajectory prediction. In *ICCV*.
- [60] Yanjun Huang, Jiatong Du, Ziru Yang, Zewei Zhou, Lin Zhang, and Hong Chen. 2022. A survey on trajectory-prediction methods for autonomous driving. *IEEE Transactions on Intelligent Vehicles* 7, 3 (2022).
- [61] Yongxian Huang, Fan Zhang, and Jinhui Hu. 2022. Deep Spatial–Temporal Graph Modeling of Urban Traffic Accident Prediction. In *The International Conference on Image, Vision and Intelligent Systems*.
- [62] Guangyu Huo, Yong Zhang, Boyue Wang, Junbin Gao, Yongli Hu, and Baocai Yin. 2023. Hierarchical Spatio–Temporal Graph Convolutional Networks and Transformer Network for Traffic Flow Forecasting. *TITS* 24, 4 (2023).
- [63] Yusen Huo, Qinghua Tao, and Jianming Hu. 2020. Cooperative control for multi-intersection traffic signal based on deep reinforcement learning and imitation learning. *IEEE Access* 8 (2020).
- [64] Hrag-Harout Jebamikyous and Rasha Kashef. 2022. Autonomous vehicles perception (avp) using deep learning: Modeling, assessment, and challenges. *IEEE Access* 10 (2022).
- [65] Hyeonseok Jeon, Junwon Choi, and Dongsuk Kum. 2020. Scale-net: Scalable vehicle trajectory prediction network under random number of interacting vehicles via edge-enhanced graph convolutional neural network. In *IROS*.
- [66] Rui Jia, Pengcheng Jiang, Lei Liu, Lizhen Cui, and Yuliang Shi. 2017. Data driven congestion trends prediction of urban transportation. *IEEE Internet of Things Journal* 5, 2 (2017).
- [67] Xiaosong Jia, Penghao Wu, Li Chen, Yu Liu, Hongyang Li, and Junchi Yan. 2023. Hdgt: Heterogeneous driving graph transformer for multi-agent trajectory prediction via scene encoding. *TPAMI* (2023).
- [68] PE Jian John Lu PHD and Lakshminarayan Rajaram. 2013. Evaluation of intelligent transportation system operations using logistic regression models. *Institute of Transportation Engineers. ITE Journal* 83, 3 (2013), 40.
- [69] Weiwei Jiang and Jiayun Luo. 2022. Graph neural network for traffic forecasting: A survey. *ESWA* 207 (2022).
- [70] Weiwei Jiang, Jiayun Luo, Miao He, and Weixi Gu. 2023. Graph Neural Network for Traffic Forecasting: The Research Progress. *ISPRS International Journal of Geo-Information* 12, 3 (2023).
- [71] Guangyin Jin, Yuxuan Liang, Yuchen Fang, Jincui Huang, Junbo Zhang, and Yu Zheng. 2023. Spatio-Temporal Graph Neural Networks for Predictive Learning in Urban Computing: A Survey. *TKDE* (2023).
- [72] Guangyin Jin, Zhexu Xi, Hengyu Sha, Yanghe Feng, and Jincui Huang. 2022. Deep multi-view graph-based network for citywide ride-hailing demand prediction. *Neurocomputing* 510 (2022).
- [73] Yiannis Kamarianakis and Poulcos Prastacos. 2003. Forecasting traffic flow conditions in an urban network: Comparison of multivariate and univariate approaches. *TRR* 1857, 1 (2003).
- [74] Leilei Kang, Guojing Hu, Hao Huang, Weiye Lu, and Lan Liu. 2020. Urban traffic travel time short-term prediction model based on spatio-temporal feature extraction. *JAT* 2020 (2020).
- [75] Ghazaleh Khodabandelou, Walid Kheriji, and Fouad Hadj Selem. 2021. Link traffic speed forecasting using convolutional attention-based gated recurrent unit. *Applied Intelligence* 51 (2021).
- [76] Thomas N Kipf and Max Welling. 2016. Variational graph auto-encoders. *arXiv preprint arXiv:1611.07308* (2016).
- [77] Thomas N Kipf and Max Welling. 2017. Semi-supervised classification with graph convolutional networks. In *ICLR*.
- [78] Philip Koopman and Michael Wagner. 2017. Autonomous vehicle safety: An interdisciplinary challenge. *ITSM* 9, 1 (2017).
- [79] Sampo Kuutti, Richard Bowden, Yaochu Jin, Phil Barber, and Saber Fallah. 2020. A survey of deep learning applications to autonomous vehicle control. *TITS* 22, 2 (2020).
- [80] Shiyong Lan, Yitong Ma, Weikang Huang, Wenwu Wang, Hongyu Yang, and Pyang Li. 2022. DSTAGNN: Dynamic Spatial-Temporal Aware Graph Neural Network for Traffic Flow Forecasting. In *ICML*.
- [81] Colin Lea, Michael D Flynn, Rene Vidal, Austin Reiter, and Gregory D Hager. 2017. Temporal convolutional networks for action segmentation and detection. In *CVPR*.
- [82] Eunkyeong Lee, Hosik Choi, Do-Gyeong Kim, et al. 2023. PGDRT: Prediction Demand Based on Graph Convolutional Network for Regional Demand-Responsive Transport. *JAT* (2023).
- [83] Kyungeun Lee, Moonjung Eo, Euna Jung, Yoonjin Yoon, and Wonjong Rhee. 2021. Short-term traffic prediction with deep neural networks: A survey. *IEEE Access* 9 (2021).
- [84] Sangsoo Lee and Daniel B Fambro. 1999. Application of subset autoregressive integrated moving average model for short-term freeway traffic volume forecasting. *TRR* 1678, 1 (1999).
- [85] Moshe Levin and Yen-Der Tsao. 1980. On forecasting freeway occupancies and volumes (abridgment). *TRR* 773 (1980).
- [86] Jia Li, Zhichao Han, Hong Cheng, Jiao Su, Pengyun Wang, Jianfeng Zhang, and Lujia Pan. 2019. Predicting path failure in time-evolving graphs. In *KDD*.

- [87] Jie Li, Fuyu Lin, Guangjie Han, Yifan Wang, Ruiyun Yu, Ann Move Oguti, and Zhenglin Li. 2023. PAG-TSN: Ridership Demand Forecasting Model for Shared Travel Services of Smart Transportation. *TITS* (2023).
- [88] Jiachen Li, Hengbo Ma, Zhihao Zhang, Jinning Li, and Masayoshi Tomizuka. 2022. Spatio-temporal graph dual-attention network for multi-agent prediction and tracking. *TITS* 23, 8 (2022).
- [89] Mengzhang Li and Zhanxing Zhu. 2021. Spatial-temporal fusion graph neural networks for traffic flow forecasting. In *AAAI*.
- [90] Ruoyu Li, Sheng Wang, Feiyun Zhu, and Junzhou Huang. 2018. Adaptive graph convolutional neural networks. In *AAAI*.
- [91] Xiaoshuang Li, Zhongzheng Guo, Xingyuan Dai, Yilun Lin, Junchen Jin, Fenghua Zhu, and Fei-Yue Wang. 2020. Deep imitation learning for traffic signal control and operations based on graph convolutional neural networks. In *ITSC*.
- [92] Xin Li, Xiaowen Ying, and Mooi Choo Chuah. 2019. Grip: Graph-based interaction-aware trajectory prediction. In *ITSC*.
- [93] Yujia Li, Daniel Tarlow, Marc Brockschmidt, and Richard Zemel. 2015. Gated graph sequence neural networks. *arXiv preprint arXiv:1511.05493* (2015).
- [94] Yun Li, Dazhou Yu, Zhenke Liu, Minxing Zhang, Xiaoyun Gong, and Liang Zhao. 2023. Graph Neural Network for spatiotemporal data: methods and applications. *arXiv preprint arXiv:2306.00012* (2023).
- [95] Yaguang Li, Rose Yu, Cyrus Shahabi, and Yan Liu. 2017. Graph Convolutional Recurrent Neural Network: Data-Driven Traffic Forecasting. (2017).
- [96] Yaguang Li, Rose Yu, Cyrus Shahabi, and Yan Liu. 2018. Diffusion Convolutional Recurrent Neural Network: Data-Driven Traffic Forecasting. In *ICLR*.
- [97] Lyuchao Liao, Ben Li, Fumin Zou, and Dejuan Huang. 2023. MFGCN: A Multimodal Fusion Graph Convolutional Network for Online Car-hailing Demand Prediction. *IEEE Intelligent Systems* (2023).
- [98] Manxi Lin and Aasa Feragen. 2022. diffconv: Analyzing irregular point clouds with an irregular view. In *European Conference on Computer Vision*. Springer.
- [99] Yangxin Lin, Ping Wang, and Meng Ma. 2017. Intelligent transportation system (ITS): Concept, challenge and opportunity. In *BigDataSecurity*.
- [100] Yi SUN Kaixiang LIN and Ali Kashif Bashir. 2023. KeyLight: Intelligent Traffic Signal Control Method Based on Improved Graph Neural Network. *IEEE Transactions on Consumer Electronics* (2023).
- [101] Zhi-Hao Lin, Sheng-Yu Huang, and Yu-Chiang Frank Wang. 2020. Convolution in the cloud: Learning deformable kernels in 3d graph convolution networks for point cloud analysis. In *CVPR*.
- [102] Haiyang Liu, Chunjiang Zhu, Detian Zhang, and Qing Li. 2023. Attention-based Spatial-Temporal Graph Convolutional Recurrent Networks for Traffic Forecasting. *arXiv preprint arXiv:2302.12973* (2023).
- [103] Jielun Liu, Ghim Ping Ong, and Xiqun Chen. 2020. GraphSAGE-based traffic speed forecasting for segment network with sparse data. *TITS* 23, 3 (2020).
- [104] Jin Liu, Naiqi Wu, Yan Qiao, and Zhiwu Li. 2021. A scientometric review of research on traffic forecasting in transportation. *IET Intelligent Transport Systems* 15, 1 (2021).
- [105] Zhi Liu, Yang Chen, Feng Xia, Jixin Bian, Bing Zhu, Guojiang Shen, and Xiangjie Kong. 2023. TAP: Traffic Accident Profiling via Multi-Task Spatio-Temporal Graph Representation Learning. *TKDD* 17, 4 (2023).
- [106] Zijian Liu, Yang Luo, Xitong Pu, Geyong Min, and Chunbo Luo. 2023. A Multi-modal Hypergraph Neural Network via Parametric Filtering and Feature Sampling. *TBD* (2023).
- [107] Dening Lu, Qian Xie, Kyle Gao, Linlin Xu, and Jonathan Li. 2022. 3DCTN: 3D convolution-transformer network for point cloud classification. *TITS* 23, 12 (2022).
- [108] Xianglong Luo, Danyang Li, Yu Yang, and Shengrui Zhang. 2019. Spatiotemporal traffic flow prediction with KNN and LSTM. *JAT* (2019).
- [109] Helmut Lütkepohl. 2005. *New introduction to multiple time series analysis*. Springer Science & Business Media.
- [110] Jiaman Ma, Jeffrey Chan, Goce Ristanoski, Sutharshan Rajasegarar, and Christopher Leckie. 2019. Bus travel time prediction with real-time traffic information. *Transportation Research Part C: Emerging Technologies* 105 (2019).
- [111] Jinming Ma and Feng Wu. 2022. Feudal Multi-Agent Reinforcement Learning with Adaptive Network Partition for Traffic Signal Control. *arXiv preprint arXiv:2205.13836* (2022).
- [112] Jinming Ma and Feng Wu. 2023. Learning to Coordinate Traffic Signals With Adaptive Network Partition. *TITS* (2023).
- [113] Zhenyu Mao, Jialong Li, Nianzhao Zheng, Kenji Tei, and Shinichi Honiden. 2021. Transfer Learning Method in Reinforcement Learning-based Traffic Signal Control. In *GCCE*.
- [114] Xiwei Mi, Chengqing Yu, Xinwei Liu, Guangxi Yan, Fuhao Yu, and Pan Shang. 2022. A dynamic ensemble deep deterministic policy gradient recursive network for spatiotemporal traffic speed forecasting in an urban road network. *Digital Signal Processing* 129 (2022).

- [115] Abdullallah Mohamed, Kun Qian, Mohamed Elhoseiny, and Christian Claudel. 2020. Social-stgcnn: A social spatio-temporal graph convolutional neural network for human trajectory prediction. In *CVPR*.
- [116] Ray Mundy. 1981. *Management of Public Transportation Systems in the 1980s:(the Emergence of Paraprivate Transportation)*. Department of Marketing and Transportation, College of Business.
- [117] Mahmoud Nazzal, Abdallah Khreishah, Joyoung Lee, and Shaahin Angizi. 2023. Semi-decentralized Inference in Heterogeneous Graph Neural Networks for Traffic Demand Forecasting: An Edge-Computing Approach. *arXiv preprint arXiv:2303.00524* (2023).
- [118] Tomoki Nishi, Keisuke Otaki, Keiichiro Hayakawa, and Takayoshi Yoshimura. 2018. Traffic signal control based on reinforcement learning with graph convolutional neural nets. In *ITSC*.
- [119] Judith Nkechinyere Njoku, Cosmas Ifeanyi Nwakanma, Gabriel Chukwunonso Amaizu, and Dong-Seong Kim. 2023. Prospects and challenges of Metaverse application in data-driven intelligent transportation systems. *IET Intelligent Transport Systems* 17, 1 (2023).
- [120] Saeed Rahmani, Asiye Baghbani, Nizar Bouguila, and Zachary Patterson. 2023. Graph Neural Networks for Intelligent Transportation Systems: A Survey. *TITS* (2023).
- [121] Honglei Ren, You Song, Jingwen Wang, Yucheng Hu, and Jinzhi Lei. 2018. A deep learning approach to the citywide traffic accident risk prediction. In *ITSC*.
- [122] Yuecheng Rong, Zhimian Xu, Ruibo Yan, and Xu Ma. 2018. Du-parking: Spatio-temporal big data tells you realtime parking availability. In *KDD*.
- [123] Amit Roy, Kashob Kumar Roy, Amin Ahsan Ali, M Ashraf Amin, and AKM Mahbubur Rahman. 2021. SST-GNN: simplified spatio-temporal traffic forecasting model using graph neural network. In *PAKDD*.
- [124] Takumi Saiki and Sachiyo Arai. 2023. Flexible Traffic Signal Control via Multi-objective Reinforcement Learning. *IEEE Access* (2023).
- [125] Abhilasha Saroj, Somdut Roy, Angshuman Guin, Michael Hunter, and Richard Fujimoto. 2018. Smart city real-time data-driven transportation simulation. In *Winter Simulation Conference*.
- [126] Franco Scarselli, Marco Gori, Ah Chung Tsoi, Markus Hagenbuchner, and Gabriele Monfardini. 2008. The graph neural network model. *IEEE Transactions on Neural Networks* 20, 1 (2008).
- [127] Farjana Islam Shashi, Salman Md Sultan, Afroza Khatun, Tangina Sultana, and Tahira Alam. 2021. A study on deep reinforcement learning based traffic signal control for mitigating traffic congestion. In *ECBIOS*.
- [128] Yiru Shen, Chen Feng, Yaoqing Yang, and Dong Tian. 2018. Mining point cloud local structures by kernel correlation and graph pooling. In *CVPR*.
- [129] Zihao Sheng, Yunwen Xu, Shibe Xue, and Dewei Li. 2022. Graph-based spatial-temporal convolutional network for vehicle trajectory prediction in autonomous driving. *TITS* 23, 10 (2022).
- [130] Tianyu Shi, Francois-Xavier Devailly, Denis Larocque, and Laurent Charlin. 2023. Improving the generalizability and robustness of large-scale traffic signal control. *arXiv preprint arXiv:2306.01925* (2023).
- [131] D Shuman, S Narang, Pascal Frossard, Antonio Ortega, and P Vanderghenyst. 2013. The Emmerging Field of Signal Processing on Graphs. *IEEE Signal Proc. Magazine* (2013).
- [132] Martin Simonovsky and Nikos Komodakis. 2017. Dynamic edge-conditioned filters in convolutional neural networks on graphs. In *CVPR*.
- [133] Chao Song, Youfang Lin, Shengnan Guo, and Huaiyu Wan. 2020. Spatial-temporal synchronous graph convolutional networks: A new framework for spatial-temporal network data forecasting. In *AAAI*.
- [134] Sainbayar Sukhbaatar, Rob Fergus, et al. 2016. Learning multiagent communication with backpropagation. In *NeurIPS*.
- [135] Zhanquan Sun and Geoffrey Fox. 2014. Traffic flow forecasting based on combination of multidimensional scaling and SVM. *International Journal of Intelligent Transportation Systems Research* 12, 1 (2014).
- [136] Joseph S Sussman. 2008. *Perspectives on intelligent transportation systems (ITS)*. Springer Science & Business Media.
- [137] Ilya Sutskever, Oriol Vinyals, and Quoc V Le. 2014. Sequence to sequence learning with neural networks. In *NeurIPS*.
- [138] Gusi Te, Wei Hu, Amin Zheng, and Zongming Guo. 2018. Rgcnn: Regularized graph cnn for point cloud segmentation. In *ACMMM*.
- [139] David Alexander Tedjopurnomo, Zhifeng Bao, Baihua Zheng, Farhana Murtaza Choudhury, and Alex Kai Qin. 2020. A survey on modern deep neural network for traffic prediction: Trends, methods and challenges. *TKDE* 34, 4 (2020).
- [140] Yongxin Tong, Yuqiang Chen, Zimu Zhou, Lei Chen, Jie Wang, Qiang Yang, Jieping Ye, and Weifeng Lv. 2017. The simpler the better: a unified approach to predicting original taxi demands based on large-scale online platforms. In *KDD*.
- [141] Jameson L Toole, Serdar Colak, Bradley Sturt, Lauren P Alexander, Alexandre Evsukoff, and Marta C González. 2015. The path most traveled: Travel demand estimation using big data resources. *Transportation Research Part C: Emerging Technologies* 58 (2015).
- [142] Luan Tran, Min Y Mun, Matthew Lim, Jonah Yamato, Nathan Huh, and Cyrus Shahabi. 2020. DeepTRANS: a deep learning system for public bus travel time estimation using traffic forecasting. *VLDB* 13, 12 (2020).

- [143] Thanh Tran, Dan He, Jiwon Kim, and Mark Hickman. 2023. MSGNN: A Multi-structured Graph Neural Network model for real-time incident prediction in large traffic networks. *Transportation Research Part C: Emerging Technologies* 156 (2023).
- [144] Lelitha Vanajakshi and Laurence R Rilett. 2004. A comparison of the performance of artificial neural networks and support vector machines for the prediction of traffic speed. In *IV*. 194–199.
- [145] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *NeurIPS*.
- [146] Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua Bengio. 2017. Graph attention networks. *arXiv preprint arXiv:1710.10903* (2017).
- [147] Matthew Veres and Medhat Moussa. 2019. Deep learning for intelligent transportation systems: A survey of emerging trends. *TITS* 21, 8 (2019).
- [148] Sandor M Veres, Levente Molnar, Nick K Lincoln, and Colin P Morice. 2011. Autonomous vehicle control systems—a review of decision making. *Proceedings of the Institution of Mechanical Engineers* 225, 2 (2011).
- [149] Eleni I Vlahogianni, John C Golias, and Matthew G Karlaftis. 2004. Short-term traffic forecasting: Overview of objectives and methods. *Transport reviews* 24, 5 (2004).
- [150] Eleni I Vlahogianni, Matthew G Karlaftis, and John C Golias. 2014. Short-term traffic forecasting: Where we are and where we’re going. *Transportation Research Part C: Emerging Technologies* 43 (2014).
- [151] Beibei Wang, Youfang Lin, Shengnan Guo, and Huaiyu Wan. 2021. GSNet: learning spatial-temporal correlations from geographical and semantic aspects for traffic accident risk forecasting. In *AAAI*.
- [152] Bao Wang, Xiyang Luo, Fangbo Zhang, Baichuan Yuan, Andrea L Bertozzi, and P Jeffrey Brantingham. 2018. Graph-based deep modeling and real time forecasting of sparse spatio-temporal data. *arXiv preprint arXiv:1804.00684* (2018).
- [153] Chu Wang, Babak Samari, and Kaleem Siddiqi. 2018. Local spectral graph convolution for point set feature learning. In *ECCV*.
- [154] Cong Wang, Yongxiang Xia, and Hui-Liang Shen. 2023. Routing and congestion in multi-modal transportation networks. *International Journal of Modern Physics C* 34, 03 (2023).
- [155] Dujuan Wang, Jiacheng Zhu, Yunqiang Yin, Joshua Ignatius, Xiaowen Wei, and Ajay Kumar. 2023. Dynamic travel time prediction with spatiotemporal features: using a GNN-based deep learning method. *Annals of Operations Research* (2023).
- [156] Min Wang, Libing Wu, Man Li, Dan Wu, Xiaochuan Shi, and Chao Ma. 2022. Meta-learning based spatial-temporal graph attention network for traffic signal control. *Knowledge-based Systems* 250 (2022).
- [157] Yang Wang, Xi Lin, Jun Wu, Ali Kashif Bashir, Wu Yang, Jianhua Li, and Muhammad Imran. 2022. Contrastive GNN-based Traffic Anomaly Analysis Against Imbalanced Dataset in IoT-based ITS. In *GLOBECOM*.
- [158] Yue Wang and Justin M Solomon. 2021. Object dgcn: 3d object detection using dynamic graphs. In *NeurIPS*.
- [159] Yue Wang, Yongbin Sun, Ziwei Liu, Sanjay E Sarma, Michael M Bronstein, and Justin M Solomon. 2019. Dynamic graph cnn for learning on point clouds. *TOG* 38, 5 (2019).
- [160] Yanan Wang, Tong Xu, Xin Niu, Chang Tan, Enhong Chen, and Hui Xiong. 2020. STMARL: A spatio-temporal multi-agent reinforcement learning approach for cooperative traffic light control. *TMC* 21, 6 (2020).
- [161] Yinhai Wang and Ziqiang Zeng. 2018. *Data-driven solutions to transportation problems*.
- [162] Zhaonan Wang, Renhe Jiang, Zekun Cai, Zipei Fan, Xin Liu, Kyoung-Sook Kim, Xuan Song, and Ryosuke Shibasaki. 2021. Spatio-temporal-categorical graph neural networks for fine-grained multi-incident co-prediction. In *CIKM*.
- [163] Chien-Hung Wei and Ying Lee. 2007. Development of freeway travel time forecasting models by integrating different sources of traffic data. *IEEE Transactions on Vehicular Technology* 56, 6 (2007).
- [164] Hua Wei, Nan Xu, Huichu Zhang, Guanjie Zheng, Xinshi Zang, Chacha Chen, Weinan Zhang, Yanmin Zhu, Kai Xu, and Zhenhui Li. 2019. Colight: Learning network-level cooperation for traffic signal control. In *CIKM*.
- [165] Yanjie Wen, Zhihong Li, Xiaoyu Wang, and Wangtu Xu. 2023. Traffic demand prediction based on spatial-temporal guided multi graph Sandwich-Transformer. *Information Sciences* 643 (2023).
- [166] Ruben Wiersma, Ahmad Nasikun, Elmar Eisemann, and Klaus Hildebrandt. 2022. Deltaconv: anisotropic operators for geometric deep learning on point clouds. *TOG* 41, 4 (2022).
- [167] Billy M Williams. 2001. Multivariate vehicular traffic flow prediction: evaluation of ARIMAX modeling. *TRR* 1776, 1 (2001).
- [168] Billy M Williams and Lester A Hoel. 2003. Modeling and forecasting vehicular traffic flow as a seasonal ARIMA process: Theoretical basis and empirical results. *Journal of Transportation Engineering* 129, 6 (2003).
- [169] JR Wootton, A Garcia-Ortiz, and SM Amin. 1995. Intelligent transportation systems: a global perspective. *Mathematical and computer modelling* 22, 4-7 (1995).
- [170] Chun-Hsin Wu, Jan-Ming Ho, and Der-Tsai Lee. 2004. Travel-time prediction with support vector regression. *T-ITS* 5, 4 (2004), 276–281.

- [171] Libing Wu, Min Wang, Dan Wu, and Jia Wu. 2021. DynSTGAT: Dynamic spatial-temporal graph attention network for traffic signal control. In *CIKM*.
- [172] Pan Wu, Zilin Huang, Yuzhuang Pian, Lunhui Xu, Jinlong Li, and Kaixun Chen. 2020. A combined deep learning method with attention-based LSTM model for short-term traffic speed forecasting. *JAT* 2020 (2020).
- [173] Zonghan Wu, Shirui Pan, Fengwen Chen, Guodong Long, Chengqi Zhang, and S Yu Philip. 2020. A comprehensive survey on graph neural networks. *TNNLS* 32, 1 (2020).
- [174] Zonghan Wu, Shirui Pan, Guodong Long, Jing Jiang, and Chengqi Zhang. 2019. Graph wavenet for deep spatial-temporal graph modeling. *arXiv preprint arXiv:1906.00121* (2019).
- [175] Tiange Xiang, Chaoyi Zhang, Yang Song, Jianhui Yu, and Weidong Cai. 2021. Walk in the cloud: Learning curves for point clouds shape analysis. In *ICCV*.
- [176] Keyulu Xu, Weihua Hu, Jure Leskovec, and Stefanie Jegelka. 2019. How powerful are graph neural networks?. In *ICLR*.
- [177] Mingxing Xu, Wenrui Dai, Chunmiao Liu, Xing Gao, Weiya Lin, Guo-Jun Qi, and Hongkai Xiong. 2020. Spatial-temporal transformer networks for traffic flow forecasting. *arXiv preprint arXiv:2001.02908* (2020).
- [178] Naganand Yadati, Madhav Nimishakavi, Prateek Yadav, Vikram Nitin, Anand Louis, and Partha Talukdar. 2019. HypergcN: A new method for training graph convolutional networks on hypergraphs. In *NeurIPS*.
- [179] Shantian Yang. 2023. Hierarchical graph multi-agent reinforcement learning for traffic signal control. *Information Sciences* 634 (2023).
- [180] Shuguan Yang, Wei Ma, Xidong Pi, and Sean Qian. 2019. A deep learning approach to real-time parking occupancy prediction in transportation networks incorporating multiple spatio-temporal data sources. *Transportation Research Part C: Emerging Technologies* 107 (2019).
- [181] Shantian Yang, Bo Yang, Zhongfeng Kang, and Lihui Deng. 2021. IHG-MA: Inductive heterogeneous graph multi-agent reinforcement learning for multi-intersection traffic signal control. *Neural Networks* 139 (2021).
- [182] Yang Yang, Xin Shao, Yuting Zhu, Enjian Yao, Dongmei Liu, Feng Zhao, et al. 2023. Short-Term Forecasting of Dockless Bike-Sharing Demand with the Built Environment and Weather. *JAT* (2023).
- [183] Jiexia Ye, Juanjuan Zhao, Kejiang Ye, and Chengzhong Xu. 2020. How to build a graph-based deep learning architecture in traffic domain: A survey. *TITS* 23, 5 (2020).
- [184] Jaehyuk Yi and Jinkyoo Park. 2020. Hypergraph convolutional recurrent neural network. In *KDD*.
- [185] Tianwei Yin, Xingyi Zhou, and Philipp Krähenbühl. 2021. Multimodal virtual point 3d detection. In *NeurIPS*.
- [186] Xueyan Yin, Genze Wu, Jinze Wei, Yanming Shen, Heng Qi, and Baocai Yin. 2021. Deep learning on traffic prediction: Methods, analysis, and future directions. *TITS* 23, 6 (2021).
- [187] Jinwon Yoon, Kyuree Ahn, Jinkyoo Park, and Hwasoo Yeo. 2021. Transferable traffic signal control: Reinforcement learning with graph centric state representation. *Transportation Research Part C: Emerging Technologies* 130 (2021).
- [188] Bing Yu, Haoteng Yin, and Zhanxing Zhu. 2018. Spatio-Temporal Graph Convolutional Networks: A Deep Learning Framework for Traffic Forecasting. In *IJCAI*.
- [189] Le Yu, Bowen Du, Xiao Hu, Leilei Sun, Liangzhe Han, and Weifeng Lv. 2021. Deep spatio-temporal graph convolutional network for traffic accident prediction. *Neurocomputing* 423 (2021).
- [190] Yong Yu, Xiaosheng Si, Changhua Hu, and Jianxun Zhang. 2019. A Review of Recurrent Neural Networks: LSTM Cells and Network Architectures. *Neural Computation* 31 (2019).
- [191] Zhengxu Yu, Shuxian Liang, Long Wei, Zhongming Jin, Jianqiang Huang, Deng Cai, Xiaofei He, and Xian-Sheng Hua. 2021. MaCAR: Urban traffic light control via active multi-agent communication and action rectification. In *IJCAI*.
- [192] Zhuoning Yuan, Xun Zhou, and Tianbao Yang. 2018. Hetero-convlstm: A deep learning approach to traffic accident prediction on heterogeneous spatio-temporal data. In *KDD*.
- [193] Zheng Zeng. 2021. GraphLight: graph-based reinforcement learning for traffic signal control. In *ICCCS*.
- [194] Shi Zhancheng. 2021. Research on application of deep reinforcement learning in traffic signal control. In *ICFSP*.
- [195] Chenhan Zhang, Shuyu Zhang, JQ James, and Shui Yu. 2021. FASTGNN: A topological information protected federated learning approach for traffic speed forecasting. *IEEE Transactions on Industrial Informatics* 17, 12 (2021).
- [196] Junhao Zhang, Juncheng Jin, Junjie Tang, and Zehui Qu. 2023. FPTN: Fast Pure Transformer Network for Traffic Flow Forecasting. In *ICANN*.
- [197] Jie Zhang, Zhihao Qu, Chenxi Chen, Haozhao Wang, Yufeng Zhan, Baoliu Ye, and Song Guo. 2021. Edge learning: The enabling technology for distributed big data analytics in the edge. *CSUR* 54, 7 (2021).
- [198] Junping Zhang, Fei-Yue Wang, Kunfeng Wang, Wei-Hua Lin, Xin Xu, and Cheng Chen. 2011. Data-driven intelligent transportation systems: A survey. *TITS* 12, 4 (2011).
- [199] Kuangen Zhang, Ming Hao, Jing Wang, Xinxing Chen, Yuquan Leng, Clarence W de Silva, and Chenglong Fu. 2021. Linked dynamic graph cnn: Learning through point cloud by linking hierarchical features. In *M2VIP*.
- [200] Kunpeng Zhang, Lan Wu, Zhaoju Zhu, and Jiang Deng. 2020. A multitask learning model for traffic flow and speed forecasting. *IEEE Access* 8 (2020).

- [201] Weijia Zhang, Hao Liu, Yanchi Liu, Jingbo Zhou, and Hui Xiong. 2020. Semi-supervised hierarchical recurrent graph neural network for city-wide parking availability prediction. In *AAAI*.
- [202] Weijia Zhang, Hao Liu, Yanchi Liu, Jingbo Zhou, Tong Xu, and Hui Xiong. 2020. Semi-supervised city-wide parking availability prediction via hierarchical recurrent graph neural network. *TKDE* 34, 8 (2020), 3984–3996.
- [203] Yang Zhang and Tao Cheng. 2020. Graph deep learning model for network-based predictive hotspot mapping of sparse spatio-temporal events. *Computers, Environment and Urban Systems* 79 (2020).
- [204] Yang Zhang, Xiangyu Dong, Lanyu Shang, Daniel Zhang, and Dong Wang. 2020. A multi-modal graph neural network approach to traffic risk forecasting in smart urban sensing. In *SECON*.
- [205] Yifei Zhang, Hao Zhu, Ziqiao Meng, Piotr Koniusz, and Irwin King. 2022. Graph-adaptive rectified linear unit for graph neural networks. In *TheWebConf*.
- [206] Ziwei Zhang, Peng Cui, and Wenwu Zhu. 2020. Deep learning on graphs: A survey. *TKDE* 34, 1 (2020).
- [207] Chenguang Zhao and Gang Wang. 2022. Dynamic Traffic Light Control with Reinforcement Learning Based on Gnn Prediction. Available at SSRN 4040526 (2022).
- [208] Dong Zhao, Chen Ju, Guanzhou Zhu, Jing Ning, Dan Luo, Desheng Zhang, and Huadong Ma. 2021. MePark: Using meters as sensors for citywide on-street parking availability prediction. *TITS* 23, 7 (2021).
- [209] Hengshuang Zhao, Li Jiang, Jiaya Jia, Philip HS Torr, and Vladlen Koltun. 2021. Point transformer. In *ICCV*.
- [210] Ling Zhao, Yujiao Song, Chao Zhang, Yu Liu, Pu Wang, Tao Lin, Min Deng, and Haifeng Li. 2019. T-GCN: A Temporal Graph Convolutional Network for Traffic Prediction. *TITS* (2019).
- [211] Tianhong Zhao, Zhengdong Huang, Wei Tu, Filip Biljecki, and Long Chen. 2023. Developing a multiview spatiotemporal model based on deep graph neural networks to predict the travel demand by bus. *IJGIS* (2023).
- [212] Yusheng Zhao, Jinyu Chen, Chen Gao, Wenguan Wang, Lirong Yang, Haibing Ren, Huaxia Xia, and Si Liu. 2022. Target-driven structured transformer planner for vision-language navigation. In *Proceedings of the 30th ACM International Conference on Multimedia*.
- [213] Yusheng Zhao, Xiao Luo, Wei Ju, Chong Chen, Xian-Sheng Hua, and Ming Zhang. 2023. Dynamic Hypergraph Structure Learning for Traffic Flow Forecasting. In *ICDE*.
- [214] Chuanpan Zheng, Xiaoliang Fan, Cheng Wang, and Jianzhong Qi. 2020. GMAN: A graph multi-attention network for traffic prediction. In *AAAI*.
- [215] Ting Zhong, Zheyang Xu, and Fan Zhou. 2021. Probabilistic graph neural networks for traffic signal control. In *ICASSP*.
- [216] Hao Zhou, Dongchun Ren, Huaxia Xia, Mingyu Fan, Xu Yang, and Hai Huang. 2021. Ast-gnn: An attention-based spatio-temporal graph neural network for interaction-aware pedestrian trajectory prediction. *Neurocomputing* 445 (2021).
- [217] Jie Zhou, Ganqu Cui, Shengding Hu, Zhengyan Zhang, Cheng Yang, Zhiyuan Liu, Lifeng Wang, Changcheng Li, and Maosong Sun. 2020. Graph neural networks: A review of methods and applications. *AI Open* 1 (2020).
- [218] Wei Zhou, Qian Wang, Weiwei Jin, Xinzhe Shi, Dekui Wang, Xingxing Hao, and Yongxiang Yu. 2023. GTNet: Graph Transformer Network for 3D Point Cloud Classification and Semantic Segmentation. *arXiv preprint arXiv:2305.15213* (2023).
- [219] Zhengyang Zhou, Yang Wang, Xike Xie, Lianliang Chen, and Hengchang Liu. 2020. RiskOracle: A minute-level citywide traffic accident forecasting framework. In *AAAI*.
- [220] Zhengyang Zhou, Yang Wang, Xike Xie, Lianliang Chen, and Chaochao Zhu. 2020. Foresee urban sparse traffic accidents: A spatiotemporal multi-granularity perspective. *TKDE* 34, 8 (2020).
- [221] Di Zhu and Yu Liu. 2018. Modelling spatial patterns using graph convolutional networks. In *GIScience*.
- [222] Lei Zhu, Tianrui Li, and Shengdong Du. 2019. Ta-stan: A deep spatial-temporal attention learning framework for regional traffic accident risk prediction. In *IJCNN*.
- [223] Wenjun Zhu, Yanghong Liu, Peng Wang, Mengyi Zhang, Tian Wang, and Yang Yi. 2023. Tri-HGNN: Learning Triple Policies Fused Hierarchical Graph Neural Networks for Pedestrian Trajectory Prediction. *PR* (2023).
- [224] Wenjie Zi, Wei Xiong, Hao Chen, and Luo Chen. 2021. TAGCN: Station-level demand prediction for bike-sharing system via a temporal attention graph convolution network. *Information Sciences* 561 (2021).