

# Graph Neural Network for Traffic Forecasting: A Survey

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**Abstract**—Traffic forecasting is important for the success of intelligent transportation systems. Deep learning models, including convolution neural networks and recurrent neural networks, have been extensively applied in traffic forecasting problems to model spatial and temporal dependencies. In recent years, to model the graph structures in transportation systems as well as contextual information, graph neural networks have been introduced and have achieved state-of-the-art performance in a series of traffic forecasting problems. In this survey, we review the rapidly growing body of research using different graph neural networks, e.g. graph convolutional and graph attention networks, in various traffic forecasting problems, e.g. road traffic flow and speed forecasting, passenger flow forecasting in urban rail transit systems, and demand forecasting in ride-hailing platforms. We also present a comprehensive list of open data and source resources for each problem and identify future research directions. To the best of our knowledge, this paper is the first comprehensive survey that explores the application of graph neural networks for traffic forecasting problems. We have also created a public GitHub repository where the latest papers, open data, and source resources will be updated.

**Index Terms**—Traffic Forecasting, Graph Neural Networks, Graph Convolution Network, Graph Attention Network, Deep Learning.

## I. INTRODUCTION

Transportation systems are among the most important infrastructure in modern cities, supporting the daily commuting and traveling of millions of people. With rapid urbanization and population growth, transportation systems have become more complex. Modern transportation systems encompass road vehicles, rail transport, and various shared travel modes that have emerged in recent years, including online ride-hailing, bike-sharing, and e-scooter sharing. Expanding cities face many transportation-related problems, including air pollution and traffic congestion. Early intervention based on traffic forecasting is seen as the key to improving the efficiency of a transportation system and to alleviate transportation-related problems. In the development and operation of smart cities and intelligent transportation systems (ITSs), traffic states are detected by sensors (e.g. loop detectors) installed on roads, subway and bus system transaction records, traffic surveillance videos, and even smartphone GPS data collected in a crowd-sourced fashion. Traffic forecasting is typically based on consideration of historical traffic state data, together

with the external factors which affect traffic states, e.g. weather and holidays.

Both short-term and long-term traffic forecasting problems for various transport modes are considered in the literature. This survey focuses on the data-driven approach, which involves forecasting based on historical data. The traffic forecasting problem is more challenging than other time series forecasting problems because it involves large data volumes with high dimensionality, as well as multiple dynamics including emergency situations, e.g. traffic accidents. The traffic state in a specific location has both spatial dependency, which may not be affected only by nearby areas, and temporal dependency, which may be seasonal. Traditional linear time series models, e.g. auto-regressive and integrated moving average (ARIMA) models, cannot handle such spatiotemporal forecasting problems. Machine learning (ML) and deep learning techniques have been introduced in this area to improve forecasting accuracy, for example, by modeling the whole city as a grid and applying a convolutional neural network (CNN) as demonstrated by [1]. However, the CNN-based approach is not optimal for traffic forecasting problems that have a graph-based form, e.g. road networks.

In recent years, graph neural networks (GNNs) have become the frontier of deep learning research, showing state-of-the-art performance in various applications [2]. GNNs are ideally suited to traffic forecasting problems because of their ability to capture spatial dependency, which is represented using non-Euclidean graph structures. For example, a road network is naturally a graph, with road intersections as the nodes and road connections as the edges. With graphs as the input, several GNN-based models have demonstrated superior performance to previous approaches on tasks including road traffic flow and speed forecasting problems. These include, for example, the diffusion convolutional recurrent neural network (DCRNN) [3] and Graph WaveNet [4] models. The GNN-based approach has also been extended to other transportation modes, utilizing various graph formulations and models.

To the best of the authors' knowledge, this paper presents the first comprehensive literature survey of GNN-related approaches to traffic forecasting problems. While several relevant traffic forecasting surveys exist [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], none are GNN-focused. For this survey, we reviewed 212 papers published in the years 2018 to 2020. Additionally, because this is a very rapidly developing research field, we also included preprints that have not yet gone through the traditional peer review process (e.g., arXiv papers) to present the latest progress. Based on these studies, we identify the most frequently

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considered problems, graph formulations, and models. We also investigate and summarize publicly available useful resources, including datasets, software, and open-sourced code, for GNN-based traffic forecasting research and application. Lastly, we identify the challenges and future directions of applying GNNs to the traffic forecasting problem. Our aim is to provide a comprehensive summary of related work and a useful starting point for new researchers in this field. In addition to this paper, we have created an open GitHub repository on this topic <sup>1</sup>, where relevant content will be updated continuously.

Our contributions are summarized as follows:

1) *Comprehensive Review*: We present the most comprehensive review of graph-based solutions for traffic forecasting problems in the past three years (2018-2020).

2) *Resource Collection*: We provide the latest comprehensive list of open datasets and code resources for replication and comparison in future work.

3) *Future Directions*: We discuss several challenges and potential future directions for researchers in this field.

The remainder of this paper is organized as follows. In Section II, we compare our work with other relevant research surveys. In Section III, we categorize the traffic forecasting problems that are involved with GNN-based models. In Section IV, we summarize the graphs and GNNs used in the reviewed studies. In Section V, we outline the open resources. Finally, in Section VI, we point out challenges and future directions.

## II. RELATED RESEARCH SURVEYS

In this section, we introduce the most recent relevant research surveys (most of which were published in 2020). The differences between our study and these existing surveys are pointed out when appropriate. We start with the surveys addressing wider ITS topics, followed by those focusing on traffic prediction problems and GNN application in particular.

A comprehensive review of deep learning models in ITSs is given in [16]. Applications discussed include prediction of traffic characteristics, traffic incident inference, vehicle incident inference, vehicle identification, traffic signal timing, ride sharing, and public transportation, and visual recognition tasks. Various deep learning models and their hardware requirements are discussed. GNN is only mentioned in the task of traffic characteristics prediction.

Both intelligent traffic sensing and prediction with deep learning are discussed in [9]. This paper provides a good introduction to the key components of ITSs and deep learning, including sensor networks, transmission technologies, deep learning models, and traffic management. The authors highlight that traffic sensing data quality significantly affects the performance of deep learning models. Missing data is a challenge that can be handled by preprocessing data or considered in the design of error-tolerant deep learning models. Among the major milestones of deep-learning driven traffic prediction (summarized in Figure 2 of [9]), the state-of-the-art models after 2019 are all based on GNNs, indicating that this is indeed the frontier of deep learning-based traffic prediction research.

In [5], three spatiotemporal sequence forecasting (STSF) categories are highlighted, namely, moving point cloud trajectory forecasting, STSF on regular grids, and STSF on irregular grids. Both classical and deep learning solutions for these problems are reviewed. The scope is beyond the traffic domain and the solution is not limited to GNNs or deep neural networks.

A taxonomy of existing traffic prediction methods, including both traditional and deep learning methods, is presented in [7]. A series of experiments are conducted using publicly available datasets for model performance comparison; and the state-of-the-art methods for prediction tasks including flow, speed, demand, occupancy, and travel time are summarized. Of GNNs, only graph convolutional networks (GCNs) are considered.

A broader concept of human mobility is reviewed in [8]. This includes tasks such as next-location prediction, crowd flow prediction, and trajectory generation. The authors provide a detailed explanation of different model structures including the CNN, recurrent neural network (RNN), generative adversarial network (GAN), and attention mechanism. Additionally, rich mobility data sources, including mobile phone data, GPS traces, social media data, and auxiliary data, are identified and discussed.

ML models for traffic prediction are categorized in [10]. These include the regression model, example-based models (e.g., k-nearest neighbors), kernel-based models (e.g. support vector machine and radial basis function), neural network models, and hybrid models. In this paper, the GNN (a type of neural network) is not explicitly and separately listed. Both relevant real-world datasets and microscopic traffic simulators are summarized. Useful information about data preprocessing and model design is presented, as well as the open challenges to inspire future work.

The benefits and disadvantages of deep learning models for short-term traffic forecasting are evaluated comprehensively, using experiments based on a variety of traffic data types, in [11]. The authors conclude that deep learning is not always the best modeling technique in practical applications, where linear models and machine learning techniques with less computational complexity can sometimes be preferable.

In [13], deep neural networks for short-term traffic prediction are roughly categorized into five different generations. The first generation is formed by restricted Boltzmann machines (RBMs) and deep belief networks (DBNs). The second generation includes multi-layer Perceptron, CNNs, and RNNs. Hybrids of CNNs and RNNs are taken as the third generation; GCNs are classified as the fourth generation; and other advanced techniques that have been considered but are not yet widely applied are merged into the fifth generation. These include transfer learning, meta learning, reinforcement learning, and the attention mechanism. Before these advanced techniques become mature in traffic prediction tasks, GNNs remain the state-of-the-art technique.

Data preparation processes and prediction methods for the urban flow prediction problem are summarized in [14]. Three groups of preparation processes are discussed: (1) collecting spatiotemporal datasets; (2) decomposing the city map; and (3) dealing with various data problems, including data missing,

<sup>1</sup><https://github.com/jwwthu/GNN4Traffic>

data imbalance, and data uncertainty. Then, five types of prediction methods are presented (1) statistics-based methods; (2) traditional machine learning methods; (3) deep learning-based methods; (4) reinforcement learning-based methods; and (5) transfer learning-based methods. GNNs are included in the deep learning-based methods in the discussion.

The various traffic prediction techniques are categorized into four types in [15], namely, machine learning (ML), computational intelligence (CI), deep learning (DL), and hybrid algorithms. Among these types, hybrid techniques are believed to perform better than the rest. However, GNN-based models are not explicitly covered.

Two specific traffic prediction problems, namely, traffic volume prediction and speed prediction, are discussed in [17]. Here, the prediction models are categorized into two types: (1) statistical models and (2) machine learning-based methods. The latter of these includes GNNs. The authors find that of these two types, statistics-based models have better model interpretability, whereas ML-based models are more flexible. Open challenges are discussed separately for these two model-types.

In [18], 37 deep neural networks for traffic prediction are reviewed, categorized, and discussed. The authors conclude that encoder-decoder long short term-memory (LSTM) combined with graph-based methods is the state-of-the-art prediction technique. A detailed explanation of various data types and popular deep neural network architectures is also provided, along with challenges and future directions for traffic prediction.

Additional research surveys consider aspects other than model selection. In [6], spatiotemporal feature selection and extraction pre-processing methods, which may also be embedded as internal model processes, are reviewed. A meta-analysis of prediction accuracy when applying deep learning methods to transport studies is given in [19]. In this study, apart from the models themselves, additional factors including sample size and prediction time horizon are shown to have a significant influence on prediction accuracy.

To the authors' best knowledge, there are no existing surveys focusing on the application of GNNs for traffic forecasting. Graph-based deep learning architectures are reviewed in [12], for a series of traffic applications, namely, traffic congestion, travel demand, transportation safety, traffic surveillance, and autonomous driving. Specific and practical guidance for constructing graphs in these applications is provided. The advantages and disadvantages of both GNNs and other deep learning models (e.g. RNN, TCN, Seq2Seq, and GAN) are examined. While the focus is not limited to traffic prediction problems, the graph construction process is universal in the traffic domain when GNNs are involved.

### III. PROBLEMS

In this section, we discuss and categorize the different types of traffic forecasting problems considered in the literature. Problems are first categorized by the traffic state to be predicted. Traffic flow, speed, and demand problems are considered separately while the remaining types are grouped

together under "other problems". Then, the problem-types are further broken down into levels according to where the traffic states are defined. These include road-level, region-level, and station-level categories. A full list of the traffic forecasting problems considered in the surveyed studies is shown in Table I.

#### A. Traffic Flow

We consider three levels of traffic flow problems in this survey, namely, road-level flow, region-level flow, and station-level flow.

Road-level flow problems are concerned with traffic volumes on a road and include *road traffic flow*, *road origin-destination (OD) Flow*, and *intersection traffic throughput*. In road traffic flow problems, the prediction target is the traffic volume that passes a road sensor or a specific location along the road within a certain time period (e.g. five minutes). In the road OD flow problem, the target is the volume between one location (the origin) and another (the destination) at a single point in time. The intersection traffic throughput problem considers the volume of traffic moving through an intersection.

Region-level flow problems consider traffic volume in a region. A city may be divided into regular regions (where the partitioning is grid-based) or irregular regions (e.g. road-based or zip-code-based partitions). These problems are classified by transport mode into *textitregional taxi flow*, *regional bike flow*, *regional ride-hailing flow*, *regional dockless e-scooter flow*, *regional OD taxi flow*, *regional OD bike flow*, and *regional OD ride-hailing flow* problems.

Station-level flow problems relate to the traffic volume measured at a physical station, for example, a subway or bus station. These problems are divided by station type into *station-level subway passenger flow*, *station-level bus passenger flow*, *station-level shared vehicle flow*, *station-level bike flow*, and *station-level railway passenger flow* problems.

Road-level traffic flow problems are further divided into cases of unidirectional and bidirectional traffic flow, whereas region-level and station-level traffic flow problems are further divided into the cases of inflow and outflow, based on different problem formulations.

#### B. Traffic Speed

We consider two levels of traffic speed problems in this survey, namely, road-level and region-level problems. We also include travel time and congestion predictions in this category because they are closely correlated to traffic speed. For example, in several studies, traffic congestion is judged by a threshold-based speed inference. The specific road-level speed problem categories considered are *road traffic speed*, *road travel time*, *traffic congestion*, and *time of arrival* problems; while the region-level speed problem considered is *regional OD taxi speed*.

#### C. Traffic Demand

Traffic demand refers to the potential demand for travel, which may or may not be fulfilled completely. For example,

TABLE I  
TRAFFIC FORECASTING PROBLEMS IN THE SURVEYED STUDIES.

Problem	Relevant Studies
Road Traffic Flow	[20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [67], [68], [69], [70], [71], [72], [73], [74]
Road OD Flow	[75], [76]
Intersection Traffic Throughput	[77]
Regional Taxi Flow	[78], [79], [80], [81], [82], [83], [84], [85]
Regional Bike Flow	[78], [79], [81], [84]
Regional Ride-hailing Flow	[83]
Regional Dockless E-Scooter Flow	[86]
Regional OD Taxi Flow	[84], [87]
Regional OD Bike Flow	[84]
Regional OD Ride-hailing Flow	[88], [89], [90]
Station-level Subway Passenger Flow	[32], [70], [82], [91], [92], [93], [94], [95], [96], [97], [98], [99], [100]
Station-level Bus Passenger Flow	[32], [70], [82]
Station-level Shared Vehicle Flow	[101]
Station-level Bike Flow	[102], [103]
Station-level Railway Passenger Flow	[104]
Road Traffic Speed	[3], [4], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [40], [54], [59], [68], [71], [80], [93], [105], [106], [107], [108], [109], [110], [111], [112], [113], [114], [115], [116], [117], [118], [119], [120], [121], [122], [123], [124], [125], [126], [127], [128], [129], [130], [131], [132], [133], [134], [135], [136], [137], [138], [139], [140], [141], [142], [143], [144], [145], [146], [147], [148], [149], [150], [151], [152], [153], [154], [155], [156], [157], [158], [159], [160], [161], [162], [163], [164], [165], [166], [167], [168], [169], [170], [171], [172], [173], [174], [175]
Road Travel Time	[23], [176], [177], [178], [179]
Traffic Congestion	[180], [181], [182], [183], [184]
Time of Arrival	[185]
Regional OD Taxi Speed	[186]
Ride-hailing Demand	[187], [188], [189], [190], [191], [192], [193], [194], [195], [196], [197]
Taxi Demand	[192], [193], [195], [198], [199], [200], [201], [202], [203], [204], [205], [206], [207]
Shared Vehicle Demand	[208]
Bike Demand	[192], [193], [195], [204], [207], [209], [210], [211], [212], [213], [214], [215], [216]
Traffic Accident	[217], [218], [219], [220]
Traffic Anomaly	[221]
Parking Availability	[222], [223], [224]
Transportation Resilience	[225]
Urban Vehicle Emission	[226]
Railway Delay	[227]
Lane Occupancy	[228]

passengers represent the demand, whereas only a subset of these requests may be served depending on the supply of drivers and vehicles, especially during rush hours. Accurate prediction of travel demand is a key element of vehicle scheduling systems (e.g. online ride-hailing or taxi dispatch platforms). However, in some cases, it is difficult to collect the potential travel demand from passengers and a compromise method using transaction records as an indication of the traffic demand is used. In such cases the real demand may be underestimated. Based on transport mode, the traffic demand problems considered include *ride-hailing demand*, *taxi demand*, *shared vehicle demand*, and *bike demand*.

#### D. Other Problems

In addition to the above three categories of traffic forecasting problems, GNNs are also being applied to the following problems.

*Traffic accident* and *Traffic anomaly*: the target is to predict the traffic accident number reported to the police system.

*Parking availability*: the target is to predict the availability of parking space in the streets or in a car parking lot.

*Transportation resilience*: defined and predicted in [225].

*Urban vehicle emission*: while not directly related to traffic states, the prediction of urban vehicle emission is considered in [226].

*Railway delay*: the delay time of specific routes in the railway system is considered in [227].

*Lane occupancy*: With simulated traffic data, lane occupancy has been measured and predicted [228].

## IV. GRAPHS AND GRAPH NEURAL NETWORKS

In this section, we summarize the types of graphs and GNNs used in the surveyed studies, focusing on GNNs that are frequently used for traffic forecasting problems. For a wider and deeper discussion of GNNs, refer to [2], [229], [230].

### A. Traffic Graphs

1) *Graph Construction*: A graph is the basic structure used in GNNs. It is defined as  $G = (V, E, A)$ , where  $V$  is the set of vertices or nodes,  $E$  is the set of edges between the nodes, and  $A$  is the adjacency matrix. Element  $a_{ij}$  of  $A$  represents the “edge weight” between nodes  $i$  and  $j$ . Both the nodes and the edges may represent different attributes in different GNN problems. For traffic forecasting, the traffic state prediction target is usually one of the node features. We divide the time axis into discrete time steps, e.g. five minutes or one hour, depending on the specific scenario. In *single step forecasting*, the traffic state in the next time step is predicted, whereas in *multiple step forecasting* the traffic state several time steps later is the prediction target. The traffic state at time step  $i$  is denoted by  $\chi_i$ , and the forecasting problem is formulated as: find the function  $f$  which generates  $y = f(\chi; G)$ , where  $y$  is the traffic state to be predicted,  $\chi = \{\chi_1, \chi_2, \dots, \chi_N\}$  is the historical traffic state defined on graph  $G$ , and  $N$  is the number of time steps in the historical window size. As mentioned in Section I, traffic states can be highly affected

on an online ride-hailing platform, the ride requests sent by

by external factors, e.g. weather and holidays. The forecasting problem formulation, extended to incorporate these external factors, takes the form  $y = f(\chi, \varepsilon; G)$ , where  $\varepsilon$  represents the external factors.

Various graph structures are used to model traffic forecasting problems depending on both the forecasting problem-type and the traffic datasets available. These graphs can be pre-defined static graphs, or dynamic graphs continuously learned from the data. The static graphs can be divided into two types, namely, natural graphs and similarity graphs. Natural graphs are based on a real-world transportation system, e.g. the road network or subway system; whereas similarity graphs are based solely on the similarity between different node attributes where nodes may be virtual stations or regions.

We categorize the existing traffic graphs into the same three levels used in Section III, namely, road-level, region-level and station-level graphs, as shown in the examples in Figures 1(a), 1(b), and 1(c), respectively.

*Road-level graphs.* These include *sensor graphs*, *road segment graphs*, *road intersection graphs*, and *road lane graphs*. Sensor graphs are based on traffic sensor data (e.g. the PeMS dataset) where each sensor is a node, and the edges are road connections. The other three graphs are based on road networks with the nodes formed by road segments, road intersections, and road lanes, respectively.

*Region-level graphs.* These include *irregular region graphs*, *regular region graphs*, and *OD graphs*. In both irregular and regular region graphs the nodes are regions of the city. Regular region graphs, which have grid-based partitioning, are listed separately because of their natural connection to previous widely used grid-based forecasting using CNNs, in which the grids may be seen as image pixels. Irregular region graphs include all other partitioning approaches, e.g. road based, or zip code based [198]. In the OD graph, the nodes are origin region - destination region pairs. In these graphs, the edges are usually defined with a spatial neighborhood or other similarities.

*Station-level graphs.* These include *subway station graphs*, *bus station graphs*, *bike station graphs*, *railway station graphs*, *car-sharing station graphs*, *parking lot graphs*, and *parking block graphs*. Usually, there are natural links between stations that are used to define the edges, e.g. subway or railway lines, or the road network.

A full list of the traffic graphs used in the surveyed studies is shown in Table II. Sensor graphs and road segment graphs are most frequently used because they are compatible with the available public datasets as discussed in Section V. It is noted that in some studies multiple graphs are used as simultaneous inputs and then fused to improve the forecasting performance [40], [101].

2) *Adjacency Matrix Construction:* Adjacency matrices are seen as the key to capturing spatial dependency in traffic forecasting [12]. While nodes may be fixed by physical constraints, the user typically has control over the design of the adjacency matrix, which can even be dynamically trained from continuously evolving data. We extend the categories of adjacency matrices used in previous studies [12] and divide

TABLE II  
TRAFFIC GRAPHS IN THE SURVEYED STUDIES.

Graph	Relevant Studies
Sensor Graph	[3], [4], [22], [24], [25], [26], [27], [28], [29], [31], [33], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [66], [67], [71], [72], [73], [74], [75], [80], [106], [110], [114], [117], [121], [122], [125], [127], [129], [130], [131], [132], [134], [137], [138], [139], [141], [142], [143], [144], [145], [146], [147], [148], [149], [150], [151], [153], [155], [159], [160], [162], [167], [170], [171], [172], [173], [225]
Road Segment Graph	[20], [23], [26], [29], [30], [34], [35], [40], [50], [61], [64], [68], [76], [93], [105], [108], [109], [112], [113], [115], [116], [118], [119], [120], [123], [124], [126], [128], [130], [131], [133], [135], [138], [139], [140], [152], [154], [156], [157], [158], [161], [163], [164], [165], [168], [169], [174], [175], [176], [177], [180], [184], [185], [203], [218]
Road Intersection Graph	[20], [21], [32], [35], [49], [51], [77], [107], [111], [118], [119], [136], [178], [183]
Road Lane Graph	[228]
Irregular Region Graph	[78], [79], [80], [166], [181], [182], [186], [189], [193], [195], [196], [199], [200], [202], [204], [205], [207], [219], [221]
Regular Region Graph	[25], [65], [69], [81], [83], [84], [85], [86], [87], [88], [90], [179], [187], [188], [190], [191], [192], [194], [197], [201], [202], [206], [217], [220], [226]
OD Graph	[89], [198]
Subway Station Graph	[32], [70], [91], [92], [93], [94], [95], [96], [97], [98], [99], [100]
Bus Station Graph	[32], [70]
Bike Station Graph	[102], [103], [204], [209], [210], [211], [212], [213], [214], [215], [216]
Railway Station Graph	[104], [227]
Car-sharing Station Graph	[101], [208]
Parking Lot Graph	[222], [224]
Parking Block Graph	[223]

them into four types, namely, road-based, distance-based, similarity-based, and dynamic matrices.

*Road-based Matrix.* This type of adjacency matrix relates to the road network and includes connection matrices, transportation connectivity matrices, and direction matrices. A connection matrix is a common way of representing the connectivity between nodes. It has a binary format, with an element value of 1 if connected and 0 otherwise. The transportation connectivity matrix is used where two regions are geographically distant but conveniently reachable by motorway, highway, or subway [12]. It also includes cases where the connection is measured by travel time between different nodes, e.g. if a vehicle can travel between two intersections in less than 5 minutes then there is an edge between the two intersections [51]. The less commonly used direction matrix takes the angle between road links into consideration.

*Distance-based Matrix.* This widely used matrix-type represents the spatial closeness between nodes. It contains two sub-types, namely, neighbor and distance matrices. In neighbor matrices, the element values are determined by whether the two regions share a common boundary (if connected the value is set to 1, generally, or 1/4 for grids, and 0 otherwise).

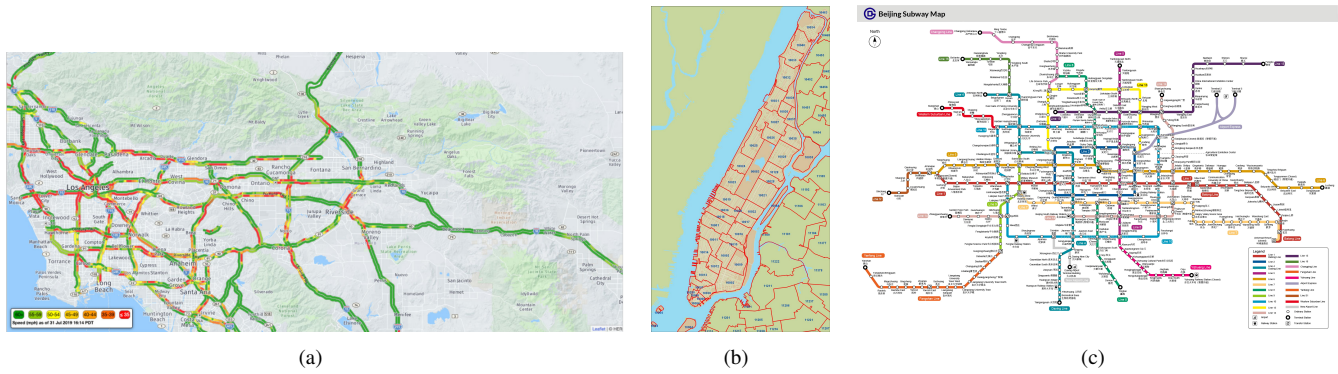


Fig. 1. Examples of the different levels of graphs. (a) a road-level graph: the road network in the Performance Measurement System (PeMS) where each sensor is a node; source: <http://pems.dot.ca.gov/>; (b) a region-level graph: the zip codes of Manhattan where each zip code zone is a node; source: <https://maps-manhattan.com/manhattan-zip-code-map>; and (c) a station-level graph, the Beijing subway system where each subway station is a node; source: <https://www.travelchinaguide.com/cityguides/beijing/transportation/subway.htm>.

In distance matrices, the element values are a function of geometrical distance between nodes. This distance may be calculated in various ways, e.g. the driving distance between two sensors, the shortest path length along the road [46], [124], or the proximity between locations calculated by the random walk with restart (RWR) algorithm [133].

*Similarity-based Matrix.* This type of matrix is divided into two sub-types, namely, traffic pattern and functional similarity matrices. Traffic pattern similarity matrices represent the correlations between traffic states, e.g. similarities of flow patterns, mutual dependencies between different locations, and traffic demand correlation in different regions. Functional similarity matrices represent, for example, the distribution of different types of point-of-interests in different regions.

*Dynamic Matrix.* This type of matrix is used when no pre-defined static matrices are used. Many studies have demonstrated the advantages of using dynamic matrices, instead of a pre-defined adjacency matrix, for various traffic forecasting problems.

A full list of the adjacency matrices applied in the surveyed studies is shown in Table III. Dynamic matrices are listed at the bottom of the table, with no further subdivisions. The connection and distance matrices are the most frequently used types, because of their simple definition and representation of spatial dependency.

### B. Graph Neural Networks

Previous neural networks, e.g. fully-connected neural networks (FNNs), CNNs, and RNNs, could only be applied to Euclidean data (i.e. images, text, and videos). As a type of neural network which directly operates on a graph structure, GNNs have the ability to capture complex relationships between objects and make inferences based on data described by graphs. GNNs have been proven effective in various node-level, edge-level, and graph-level prediction tasks. As mentioned in Section II, GNNs are currently considered the state-of-the-art techniques for traffic forecasting problems.

GNNs can be divided into four types, namely, recurrent GNNs, convolutional GNNs, graph autoencoders, and spatiotemporal GNNs [2]. Because traffic forecasting is a spa-

TABLE III  
ADJACENCY MATRICES IN THE SURVEYED STUDIES.

Adjacency Matrix	Relevant Studies
Connection Matrix	[20], [21], [22], [23], [30], [34], [36], [43], [49], [55], [57], [60], [61], [64], [65], [67], [75], [77], [89], [96], [97], [98], [100], [104], [105], [109], [111], [112], [113], [115], [118], [119], [120], [123], [130], [131], [138], [139], [144], [146], [150], [151], [152], [154], [156], [158], [161], [162], [163], [166], [168], [177], [178], [179], [183], [185], [201], [202], [203], [210], [217], [218], [221], [222], [224], [227]
Transportation Connectivity Matrix	[25], [26], [40], [51], [99], [191], [194], [208], [228]
Direction Matrix	[108], [124], [135]
Neighbor Matrix	[81], [87], [88], [90], [186], [191], [192], [196], [198], [199], [200], [213]
Distance Matrix	[3], [24], [25], [26], [27], [28], [33], [37], [38], [44], [46], [52], [53], [56], [58], [60], [62], [63], [66], [71], [72], [73], [74], [78], [80], [86], [91], [101], [102], [103], [108], [110], [121], [122], [124], [125], [127], [129], [132], [133], [135], [136], [137], [140], [141], [142], [143], [145], [147], [149], [153], [155], [159], [171], [172], [173], [175], [181], [182], [188], [189], [190], [194], [196], [197], [198], [208], [209], [212], [214], [215], [216], [223], [225], [226]
Traffic Pattern Similarity Matrix	[40], [71], [73], [78], [79], [84], [86], [91], [94], [98], [102], [103], [163], [167], [180], [184], [188], [189], [190], [193], [195], [197], [198], [209], [210], [213], [215], [216], [220]
Functional Similarity Matrix	[40], [86], [88], [101], [121], [122], [127], [188], [191], [194], [198], [208], [219]
Dynamic Matrix	[4], [31], [32], [35], [39], [41], [45], [47], [48], [50], [54], [59], [68], [69], [82], [83], [88], [92], [95], [106], [114], [116], [117], [126], [137], [157], [160], [170], [174], [187], [189], [204], [205], [206], [207]

tiotemporal problem, the GNNs used in this field can all be categorized as the latter. However, certain components of the other types of GNNs have also been applied in the surveyed traffic forecasting studies.

Spatiotemporal GNNs can be further categorized based on the approach used to capture the temporal dependency in particular. Most of the relevant studies in the literature can be split into two types, namely, *RNN-based* and *CNN-based* spatiotemporal GNNs [2]. The RNN-based approach is used

in [3], [23], [25], [26], [27], [28], [29], [30], [31], [33], [34], [38], [40], [42], [43], [44], [46], [48], [49], [51], [53], [54], [57], [59], [63], [64], [67], [68], [70], [71], [74], [76], [78], [81], [82], [83], [84], [85], [88], [89], [90], [95], [98], [99], [101], [103], [104], [105], [110], [111], [113], [114], [115], [117], [118], [123], [128], [130], [131], [132], [133], [136], [139], [141], [147], [150], [152], [154], [156], [157], [162], [167], [168], [169], [173], [174], [178], [179], [181], [182], [186], [187], [190], [194], [195], [197], [198], [199], [201], [202], [203], [204], [206], [207], [208], [209], [210], [212], [214], [216], [220], [221], [222], [223], [224], [225], [228]; while the CNN-based approach is used in [4], [32], [35], [37], [39], [41], [45], [47], [52], [56], [58], [62], [72], [80], [93], [96], [100], [106], [116], [124], [135], [137], [144], [151], [153], [155], [158], [159], [163], [170], [171], [172], [180], [185], [200], [217], [218], [226], [227].

With the recent expansion of relevant studies, we add two sub-types of spatiotemporal GNNs in this survey, namely, *attention-based* and *FNN-based*. Attention mechanism is firstly proposed to memorize long source sentences in neural machine translation [231]. Then it is used for temporal forecasting problems. As a special case, Transformer is built entirely upon attention mechanisms, which makes it possible to access any part of a sequence regardless of its distance to the target [66], [142], [188], [205]. The attention-based approaches are used in [24], [61], [65], [66], [142], [143], [145], [160], [177], [188], [193], [205], [219], while the simpler FNN-based approach is used in [20], [21], [36], [55], [60], [69], [79], [86], [87], [91], [92], [94], [102], [119], [121], [122], [126], [127], [134], [140], [161], [191], [211], [215]. Apart from using neural networks to capture temporal dependency, other techniques that have also been combined with GNNs include autoregression [192], Markov processes [138], and Kalman filters [75].

Of the additional GNN components adopted in the surveyed studies, convolutional GNNs are the most popular, while recurrent GNNs [232] and graph autoencoders [233] are used less frequently. We further categorize convolutional GNNs into the following five types: (1) graph convolutional network (GCN) [234], (2) diffusion graph convolution (DGC) [235], (3) message passing [236], (4) GraphSAGE [237], and (5) graph attention network (GAT) [238].

GCNs are spectral-based convolutional GNNs, in which the graph convolutions are defined by introducing filters from graph signal processing. Spectral convoluted neural networking [239] assumes that the filter is a set of learnable parameters and considers graph signals with multiple channels. The GCN is a first-order approximation of Chebyshev's spectral CNN (ChebNet) [240], which approximates the filter using the Chebyshev polynomials of the diagonal matrix of eigenvalues.

The alternative approach is spatial-based convolutional GNNs, in which the graph convolutions are defined by information propagation. DGC, message passing, GraphSAGE, and GAT all follow this approach. The graph convolution is modeled as a diffusion process with a transition probability from one node to a neighboring node in DGC. An equilibrium is expected to be obtained after several rounds of information transition. The general framework followed is a message

passing network, which models the graph convolutions as an information-passing process from one node to another connected node directly. To alleviate the computation problems caused by a large number of neighbors, sampling is used to obtain a fixed number of neighbors in GraphSAGE. Lastly, without using a predetermined adjacency matrix, the attention mechanism is used to learn the relative weights between two connected nodes in GAT.

A full list of the GNN components used in the surveyed studies is shown in Table IV. Currently, the most widely used GNN is the GCN. However, we also notice a growing trend in the use of GAT in traffic forecasting.

TABLE IV  
GNNs IN THE SURVEYED STUDIES.

GNN	Relevant Studies
Recurrent GNNs	[34], [81], [118], [128]
Graph Autoencoders	[22], [49], [146], [179]
GCN	[4], [20], [23], [27], [29], [30], [31], [32], [35], [36], [37], [38], [40], [44], [45], [47], [48], [50], [52], [54], [55], [56], [57], [58], [60], [61], [62], [63], [64], [65], [67], [68], [70], [71], [73], [74], [75], [76], [78], [79], [82], [83], [84], [85], [86], [87], [88], [89], [91], [92], [93], [94], [95], [96], [98], [99], [101], [103], [104], [105], [106], [107], [110], [111], [112], [115], [116], [119], [120], [121], [122], [123], [124], [126], [127], [130], [131], [133], [134], [135], [136], [138], [139], [140], [142], [144], [145], [149], [150], [152], [154], [155], [156], [157], [161], [162], [163], [164], [165], [166], [167], [168], [169], [170], [171], [172], [173], [174], [178], [180], [181], [182], [183], [184], [185], [186], [189], [190], [191], [193], [194], [195], [196], [197], [198], [199], [200], [202], [203], [204], [205], [207], [208], [209], [210], [211], [212], [213], [214], [215], [216], [217], [218], [219], [220], [221], [222], [223], [224], [226], [227]
DGC	[3], [28], [39], [42], [100], [132], [137], [141], [143], [147], [159], [175], [225]
Message Passing	[21], [37], [90]
GraphSAGE	[109]
GAT	[24], [25], [26], [33], [41], [43], [45], [46], [51], [53], [59], [66], [69], [72], [102], [106], [114], [117], [129], [151], [153], [158], [160], [172], [177], [187], [188], [201], [206], [228]

## V. OPEN DATA AND SOURCE RESOURCES

In this section, we summarize the open data and source code used in the surveyed papers.

### A. Open Data

We categorize the data used in the surveyed studies into the following types.

*Transportation Network Data.* These data represent the underlying transportation infrastructure, e.g., road, subway, and bus networks. They can be obtained from government transportation departments or extracted from online map services, e.g., OpenStreetMap.

*Traffic Sensor Data.* Traffic sensors, e.g. loop detectors, are installed on roads to collect traffic information, e.g., traffic volume or speed. This type of data is widely used for traffic prediction, especially road traffic flow and speed prediction problems.



*GPS Trajectory Data.* Different types of vehicles (e.g. taxis, buses, online ride-hailing vehicles, and shared bikes) can be equipped with GPS receivers, which record GPS coordinates in 2-60 second intervals. The trajectory data calculated from these GPS coordinate samples can be matched to road networks and further used to derive traffic flow or speed.

*Location-based Service Data.* GPS function is also embedded in smartphones, which can be used to collect various types of location-related data, e.g., check-in data, point-of-interest data, and route navigation application data.

*Trip Record Data.* These include departure and arrival dates/times, departure and arrival locations, and other trip information. Traffic speed and demand can be derived from trip record data from various sources, e.g., taxis, ride-hailing services, buses, bikes, or even dock-less e-scooters used in [86]. These data are easily collected, for example, by AFC (Automatic Fare Collection) in the subway and bus systems.

*Traffic Report Data.* This type of data is often used for abnormal cases, e.g., anomaly report data used in [221] and traffic accident report data used in [217], [219], [220].

*Multimedia Data.* This type of data can be used as an additional input to deep learning models or for verifying the traffic status indicated by other data sources. Multimedia data used in the surveyed studies include the Baidu street-view images used in [183] for traffic congestion, as well as satellite imagery data [219], and video surveillance data [178].

*Meteorological or Weather Data.* Traffic states are highly affected by the meteorological factors including temperature, humidity, precipitation, barometer pressure, and wind strength.

*Calendar Data.* This includes the information on weekends and holidays. Because traffic patterns vary significantly between weekdays and weekends/holidays, some studies consider these two cases separately.

*Simulated Traffic Data.* In addition to observed real-world datasets, microscopic traffic simulators are also used to build virtual training and testing datasets for deep learning models. Examples in the surveyed studies include the MATES Simulator used in [42] and INTEGRATION software used in [76].

While present road network and weather data can be easily found on the Internet, it is much more difficult to source historical traffic data, both due to data privacy concerns and the transmission and storage requirements of large data volumes. In Table V we present a list of the open data resources used in the surveyed studies. Most of these open data are already cleaned or preprocessed and can be readily used for benchmarking and comparing the performance of different models in future work.

1) *Traffic Sensor Data:* The relevant open traffic sensor data are listed as follows.

*METR-LA*<sup>2</sup>: This dataset contains traffic speed and volume collected from the highway of the Los Angeles County road network, with 207 loop detectors. The samples are aggregated in 5-minute intervals. The most frequently referenced time period for this dataset is from March 1st to June 30th, 2012.

*Performance Measurement System (PeMS) Data*<sup>3</sup>: This dataset contains raw detector data from over 18,000 vehicle

TABLE V  
OPEN DATA FOR TRAFFIC PREDICTION PROBLEMS.

Dataset Name	Relevant Studies
METR-LA	[3], [4], [22], [25], [26], [27], [35], [38], [43], [44], [55], [57], [71], [72], [80], [105], [110], [117], [125], [129], [132], [137], [138], [141], [142], [143], [144], [145], [146], [148], [149], [153], [155], [159], [160], [172]
PeMS all	[28], [147]
PeMS-BAY	[3], [4], [24], [25], [26], [37], [38], [43], [44], [54], [55], [66], [71], [72], [125], [132], [134], [137], [138], [141], [142], [143], [144], [145], [148], [151], [153], [155], [159], [160], [172]
PeMSD3	[36], [55], [60], [62], [71]
PeMSD4	[31], [33], [35], [36], [39], [45], [47], [48], [53], [55], [58], [59], [61], [62], [63], [67], [68], [71], [73], [74], [121], [122], [127], [173]
PeMSD7	[29], [33], [36], [37], [45], [52], [55], [56], [57], [60], [62], [63], [66], [71], [114], [121], [122], [127], [134], [173]
PeMSD8	[31], [33], [36], [39], [47], [53], [55], [58], [59], [61], [62], [68], [71]
Seattle Loop	[131], [139], [150], [167]
T-Drive	[25], [26]
SHSpeed	[29], [34], [115]
TaxiBJ	[69], [81], [193]
TaxiSZ	[105], [130]
TaxiCD	[186], [199]
TaxiNYC	[69], [79], [83], [186], [188], [189], [200], [201], [202], [204], [205], [207], [220]
UberNYC	[188], [196]
DiDiChengdu	[50], [64], [65], [83], [89], [136], [197]
DiDiTTCchengdu	[163]
DiDiXi'an	[64], [136]
DiDiHaikou	[187], [190]
BikeDC	[79], [210]
BikeNYC	[69], [79], [81], [102], [103], [192], [193], [204], [207], [210], [214], [216]
BikeChicago	[103]
SHMetro	[98]
HZMetro	[98]

detector stations on the freeway system spanning all major metropolitan areas of California from 2001 to 2019, collected with various sensors including inductive loops, side-fire radar, and magnetometers. The samples are captured every 30 seconds and aggregated in 5-minute intervals. Each data sample contains a timestamp, station ID, district, freeway ID, direction of travel, total flow, and average speed. Different subsets of PeMS data have been used in previous studies, for example:

- PeMS-BAY<sup>4</sup>: This subset contains data from 325 sensors in the Bay Area from January 1st to June 30th, 2017.
- PeMSD3: This subset uses 358 sensors in the North Central Area. The frequently referenced time period for this dataset is September 1st to November 30th, 2018.
- PeMSD4: This subset uses 307 sensors in the San Francisco Bay Area. The frequently referenced time period for this dataset is January 1st to February 28th, 2018.
- PeMSD7: This subset uses 883 sensors in the Los Angeles Area. The frequently referenced time period for this dataset is May to June, 2012.
- PeMSD8: This subset uses 170 sensors in the San Bernardino Area. The frequently referenced time period for this dataset is July to August, 2016.

<sup>2</sup>Download link: <https://github.com/liyaguang/DCRNN>

<sup>3</sup><http://pems.dot.ca.gov/>

<sup>4</sup>Download link: <https://github.com/liyaguang/DCRNN>



*Seattle Loop*<sup>5</sup>: This dataset was collected by inductive loop detectors deployed on four connected freeways (I-5, I-405, I-90, and SR-520) in the Seattle area, from January 1st to 31st, 2015. It contains the traffic speed data from 323 detectors. The samples are aggregated in 5-minute intervals.

2) *Taxi Data*: The open taxi datasets used in the surveyed studies are listed as follows.

*T-drive* [241]: This dataset contains a large number of taxicab trajectories collected by 30,000 taxis in Beijing from February 1st to June 2nd, 2015.

*SHSpeed (Shanghai Traffic Speed)* [34]<sup>6</sup>: This dataset contains 10-minute traffic speed data, derived from raw taxi trajectory data, collected from 1 to 30 April 2015, for 156 urban road segments in the central area of Shanghai, China.

*TaxiBJ* [242]: This dataset contains inflow and outflow data derived from GPS data in more than 34,000 taxicabs in Beijing from four time intervals: (1) July 1st to October 30th, 2013; (2) March 1st to June 30th, 2014; (3) March 1st to June 30th, 2015; and (4) November 1st, 2015 to April 10th, 2016. The Beijing city map is divided into  $32 \times 32$  grids and the time interval of the flow data is 30 minutes.

*TaxiSZ* [130]<sup>7</sup>: This dataset is derived from taxi trajectories in Shenzhen from January 1st to 31st, 2015. It contains the traffic speed on 156 major roads of the Luohu District every 15 minutes.

*TaxiCD*<sup>8</sup>: This dataset contains 1.4 billion GPS records from 14,864 taxis collected from August 3rd to 30th, 2014 in Chengdu, China. Each GPS record consists of a taxi ID, latitude, longitude, an indicator of whether the taxi is occupied, and a timestamp.

*TaxiNYC*<sup>9</sup>: The taxi trip records in New York starting from 2009, in both yellow and green taxis. Each trip record contains pick-up and drop-off dates/times, pick-up and drop-off locations, trip distances, itemized fares, rate types, payment types, and driver-reported passenger counts.

3) *Ride-hailing Data*: The open ride-hailing data used in the surveyed studies are listed as follows.

*UberNYC*<sup>10</sup>: This dataset comes from Uber, which is one of the largest online ride-hailing companies in the USA, and is provided by the NYC Taxi & Limousine Commission (TLC). It contains data from over 4.5 million Uber pickups in New York City from April to September 2014, and 14.3 million more Uber pickups from January to June 2015.

*Didi GAIA Open Data*<sup>11</sup>: This open data plan is supported by Didi Chuxing, which is one of the largest online ride-hailing companies in China.

- *DiDiChengdu*: This dataset contains the trajectories of DiDi Express and DiDi Premier drivers within Chengdu, China. The data contains trips from October to November 2016.

- *DiDiTTIChengdu*: This dataset represents the DiDi Travel Time Index Data in Chengdu, China in the year of 2018, which contains the average speed of major roads every 10 minutes.
- *DiDiXi'an*: This dataset contains the trajectories of DiDi Express and DiDi Premier drivers within Xi'an, China. The data contains trips from October to November 2016.
- *DiDiHaikou*: The dataset contains DiDi Express and DiDi Premier orders from May 1st to October 31st, 2017 in the city of Haikou, China, including the coordinates of origins and destinations, pickup and drop-off timestamps, as well as other information.

4) *Bike Data*: The open bike data used in the surveyed studies are listed as follows.

*BikeNYC*<sup>12</sup>: This dataset is from the NYC Bike System, which contains 416 stations. The frequently referenced time period for this dataset is from 1st July, 2013 to 31st December, 2016.

*BikeDC*<sup>13</sup>: This dataset is from the Washington D.C. Bike System, which contains 472 stations. Each record contains trip duration, start and end station IDs, and start and end times.

*BikeChicago*<sup>14</sup>: This dataset is from the Divvy System Data in Chicago, from 2015 to 2020.

5) *Subway Data*: The subway data referenced in the surveyed studies are listed as follows.

*SHMetro* [98]<sup>15</sup>: This dataset is derived from 811.8 million transaction records of the Shanghai metro system collected from July 1st to September 30th, 2016. It contains 288 metro stations and 958 physical edges. The inflow and outflow of each station are provided in 15 minute intervals.

*HZMetro* [98]<sup>16</sup>: This dataset is similar to SHMetro, from the metro system in Hangzhou, China, in January 2019. It contains 80 metro stations and 248 physical edges, and the aggregation time length is also 15 minutes.

## B. Open Source Codes

Several open source frameworks for implementing general deep learning models, most of which are built with the Python programming language, can be accessed online, e.g. TensorFlow<sup>17</sup>, Keras<sup>18</sup>, PyTorch<sup>19</sup>, and MXNet<sup>20</sup>. Additional Python libraries designed for implementing GNNs are available. These include DGL<sup>21</sup>, pytorch\_geometric<sup>22</sup>, and Graph Nets<sup>23</sup>.

Many authors have also released open-source implementations of their proposed models. The open source projects for traffic flow, traffic speed, traffic demand, and other problems

<sup>12</sup> <https://www.citibikenyc.com/system-data>

<sup>13</sup> <https://www.capitalbikeshare.com/system-data>

<sup>14</sup> <https://www.divvybikes.com/system-data>

<sup>15</sup> Download link: <https://github.com/ivechan/PVCGN>

<sup>16</sup> Download link: <https://github.com/ivechan/PVCGN>

<sup>17</sup> <https://www.tensorflow.org/>

<sup>18</sup> <https://keras.io/>

<sup>19</sup> <https://pytorch.org/>

<sup>20</sup> <https://mxnet.apache.org/>

<sup>21</sup> <https://www.dgl.ai/>

<sup>22</sup> <https://pytorch-geometric.readthedocs.io/>

<sup>23</sup> [https://github.com/deepmind/graph\\_nets](https://github.com/deepmind/graph_nets)

<sup>5</sup> Download link: <https://github.com/zhiyongc/Seattle-Loop-Data>

<sup>6</sup> Download link: <https://github.com/xxArbiter/grnn>

<sup>7</sup> Download link: <https://github.com/lehaifeng/T-GCN>

<sup>8</sup> <https://js.dclab.run/v2/cmptDetail.html?id=175>

<sup>9</sup> [http://www.nyc.gov/html/tlc/html/about/trip\\_record\\_data.shtml](http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml)

<sup>10</sup> <https://github.com/fivethirtyeight/uber-tlc-foil-response>

<sup>11</sup> <https://outreach.didichuxing.com/research/opendata/>

are summarized in Tables VI, VII, VIII, and IX, respectively. In these open source projects, TensorFlow and PyTorch are the two frameworks that are used most frequently.

## VI. CHALLENGES AND FUTURE DIRECTIONS

In this section, we discuss general challenges for traffic prediction problems as well as specific new challenges when GNNs are involved. Based on these challenges, we discuss possible future directions as well as early attempts in these directions.

### A. Challenges

1) *Heterogeneous Data*: Traffic prediction problems involve both spatiotemporal data and external factors, e.g., weather and calendar information. Heterogeneous data fusion is a challenge that is not limited to the traffic domain. GNNs have enabled significant progress by taking the underlying graph structures into consideration. However, some challenges remain; for example, geographically close nodes may not be the most influential.

Data quality concerns present an additional challenge with problems such as missing data, sparse data and noise potentially compromising forecasting results. Most of the surveyed models are only evaluated with processed high-quality datasets. A few studies do, however, take data quality related problems into consideration, e.g., using the Kalman filter to deal with the sensor data bias and noise [162], infilling missing data with moving average filters [176] or linear interpolation [161], [162]. For the missing data problem, GCNs have also been proposed to fill data gaps in OD flow problems [243].

Traffic anomalies (e.g., congestion) are an important external factor that may affect prediction accuracy and it has been proven that under congested traffic conditions a deep neural network may not perform as well as under normal traffic conditions [244]. However, it remains a challenge to collect enough anomaly data to train deep learning models (including GNNs) in both normal and anomalous situations. The same concern applies for social events, public holidays, etc.

2) *Multi-task Performance*: For the public service operation of ITSs, a multi-task framework is necessary to incorporate all the traffic information and predict the demand of multiple transportation modes simultaneously. For example, knowledge adaption is proposed to adapt the relevant knowledge from an information-intensive source to information-sparse sources for demand prediction [245]. Related challenges lie in data format incompatibilities as well as the inherent differences in spatial or temporal patterns. While some of the surveyed models can be used for multiple tasks, e.g., traffic flow and traffic speed prediction on the same road segment, most can only be trained for a single task at one time. Some efforts that have been made in GNN-based models for multi-task prediction include taxi departure flow and arrival flow [203], region-flow and transition-flow [65], crowd flows, and OD of the flows [84]. Nonetheless, GNN multi-task prediction for different types of traffic forecasting problems is a research direction requiring significant further development.

3) *Practical Implementation*: A number of challenges prevent the practical implementation of the models developed in the surveyed studies in city-scale ITSs.

First, there is significant bias introduced by the small amount of data considered in the existing studies which, in most cases, spans less than one year. The proposed solutions are therefore not necessarily applicable to different time periods or different places.

A second challenge is the computation scalability. To avoid the huge computation requirements of the large-scale real-world traffic network graphs, only a subset of the nodes and edges are typically considered. For example, most studies only use a subset of the PeMS dataset when considering the road traffic flow or speed problems. Their results can therefore only be applied to the selected subsets. Graph partitioning and parallel computing infrastructures have been proposed for solving this problem. The traffic speed and flow of the entire PeMS dataset with 11,160 traffic sensor locations are predicted simultaneously in [28], using a graph-partitioning method that decomposes a large highway network into smaller networks and trains a single DCRNN model on a cluster with graphics processing units (GPUs). However, increased modeling power can only improve the state-of-the-art results with narrow performance margins, compared to statistical and machine learning models with less complex structures and computational requirements.

A third challenge is presented by changes in the transportation networks and infrastructure. The real-world network graphs change when road segments or bus lines are added or removed. Points-of-interest in a city also change when new facilities are built. Static graph formulations are not enough for handling these situations. Some efforts have been made to solve this problem with promising results. For example, a dynamic Laplacian matrix estimator is proposed to find the change of Laplacian matrix, according to changes in spatial dependencies hidden in the traffic data [116], and a Data Adaptive Graph Generation (DAGG) module is proposed to infer the inter-dependencies between different traffic series automatically, without using pre-defined graphs based on spatial connections [31].

4) *Model Interpretation*: The challenge of model interpretation is a point of criticism for all "black-box" machine learning or deep learning models, and traffic forecasting tasks are no exception [246], [247]. The development of post-processing techniques to explain the predictions made by GNNs is still in an early phase [248], [249], [250] and the application of these techniques to the traffic forecasting domain has not yet been addressed.

### B. Future Directions

1) *Centralized Data Repository*: A centralized data repository for GNN-based traffic forecasting resources would facilitate objective comparison of the performance of different models and be an invaluable contribution to the field. Some criteria for building such data repositories, e.g. a unified data format, tracking of dataset versions, public code and ranked results, and sufficient record lengths (longer than a

TABLE VI  
OPEN SOURCE PROJECTS FOR TRAFFIC FLOW RELATED PROBLEMS.

Article	Year	Framework	Problem	Link
[24]	2020	TensorFlow	Road Traffic Flow, Road Traffic Speed	<a href="https://github.com/zhengchuanpan/GMAN">https://github.com/zhengchuanpan/GMAN</a>
[31]	2020	PyTorch	Road Traffic Flow	<a href="https://github.com/LeiBAI/AGCRN">https://github.com/LeiBAI/AGCRN</a>
[36]	2020	MXNet	Road Traffic Flow	<a href="https://github.com/wanhuiyu/STSGCN">https://github.com/wanhuiyu/STSGCN</a>
[45]	2020	TensorFlow	Road Traffic Flow	<a href="https://github.com/sam101340/GAGCN-BC-20200720">https://github.com/sam101340/GAGCN-BC-20200720</a>
[62]	2020	MXNet, PyTorch	Road Traffic Flow	<a href="https://github.com/zkx741481546/Auto-STGCN">https://github.com/zkx741481546/Auto-STGCN</a>
[68]	2020	PyTorch	Road Traffic Flow, Road Traffic Speed	<a href="https://github.com/guokan987/DGCN">https://github.com/guokan987/DGCN</a>
[71]	2020	MXNet	Road Traffic Flow, Road Traffic Speed	<a href="https://github.com/MengzhangLI/STFGNN">https://github.com/MengzhangLI/STFGNN</a>
[72]	2020	PyTorch, DGL	Road Traffic Flow	<a href="https://github.com/Kelang-Tian/ST-MGAT">https://github.com/Kelang-Tian/ST-MGAT</a>
[75]	2020	TensorFlow	Road OD Flow	<a href="https://github.com/alzmx/OD_Prediction">https://github.com/alzmx/OD_Prediction</a>
[82]	2020	Keras	Road Station-level Subway Passenger Flow, Station-level Bus Passenger Flow, Regional Taxi Flow	<a href="https://github.com/RingBDStack/GCNN-In-Traffic">https://github.com/RingBDStack/GCNN-In-Traffic</a>
[85]	2020	Pytorch	Regional Taxi Flow	<a href="https://github.com/Stanislas0/ToGCN-V2X">https://github.com/Stanislas0/ToGCN-V2X</a>
[87]	2020	PyTorch	Regional OD Taxi Flow	<a href="https://github.com/FelixOpolka/Mobility-Flows-Neural-Networks">https://github.com/FelixOpolka/Mobility-Flows-Neural-Networks</a>
[95]	2020	Keras	Station-level Subway Passenger Flow	<a href="https://github.com/JinleiZhangBJTU/ResNet-LSTM-GCN">https://github.com/JinleiZhangBJTU/ResNet-LSTM-GCN</a>
[96]	2020	Keras	Station-level Subway Passenger Flow	<a href="https://github.com/JinleiZhangBJTU/Conv-GCN">https://github.com/JinleiZhangBJTU/Conv-GCN</a>
[98]	2020	PyTorch	Station-level Subway Passenger Flow	<a href="https://github.com/ivechan/PVCGN">https://github.com/ivechan/PVCGN</a>
[99]	2020	Keras	Station-level Subway Passenger Flow	<a href="https://github.com/start2020/Multi-STGCnet">https://github.com/start2020/Multi-STGCnet</a>
[26]	2019	MXNet, DGL	Road Traffic Flow, Road Traffic Speed	<a href="https://github.com/panzheyi/ST-MetaNet">https://github.com/panzheyi/ST-MetaNet</a>
[47]	2019	MXNet	Road Traffic Flow	<a href="https://github.com/wanhuiyu/ASTGCN">https://github.com/wanhuiyu/ASTGCN</a>
[47]	2019	PyTorch	Road Traffic Flow	<a href="https://github.com/wanhuiyu/ASTGCN-r-pytorch">https://github.com/wanhuiyu/ASTGCN-r-pytorch</a>
[34]	2018	PyTorch	Road Traffic Flow	<a href="https://github.com/xxArbiter/grnn">https://github.com/xxArbiter/grnn</a>
[56]	2018	TensorFlow	Road Traffic Flow	<a href="https://github.com/VeritasYin/STGCN_IJCAI-18">https://github.com/VeritasYin/STGCN_IJCAI-18</a>
[92]	2018	Keras	Station-level Subway Passenger Flow	<a href="https://github.com/RingBDStack/GCNN-In-Traffic">https://github.com/RingBDStack/GCNN-In-Traffic</a>
[103]	2018	TensorFlow	Bike Flow	<a href="https://github.com/Di-Chai/GraphCNN-Bike">https://github.com/Di-Chai/GraphCNN-Bike</a>

TABLE VII  
OPEN SOURCE PROJECTS FOR TRAFFIC SPEED RELATED PROBLEMS.

Article	Year	Framework	Problem	Link
[69]	2020	Keras	Road Traffic Speed	<a href="https://github.com/jillbetty001/ST-CGA">https://github.com/jillbetty001/ST-CGA</a>
[105]	2020	TensorFlow	Road Traffic Speed	<a href="https://github.com/lehaifeng/T-GCN/tree/master/A3T">https://github.com/lehaifeng/T-GCN/tree/master/A3T</a>
[129]	2020	TensorFlow	Road Traffic Speed	<a href="https://github.com/fanyang01/relational-ssm">https://github.com/fanyang01/relational-ssm</a>
[144]	2020	PyTorch	Road Traffic Speed	<a href="https://github.com/nanzhan/MTGNN">https://github.com/nanzhan/MTGNN</a>
[147]	2020	TensorFlow	Road Traffic Speed	<a href="https://github.com/tanwimallick/TL-DCRNN">https://github.com/tanwimallick/TL-DCRNN</a>
[162]	2020	PyTorch	Road Traffic Speed	<a href="https://github.com/Fanglanc/DKFN">https://github.com/Fanglanc/DKFN</a>
[163]	2020	PyTorch	Road Traffic Speed	<a href="https://github.com/RobinLu1209/STAG-GCN">https://github.com/RobinLu1209/STAG-GCN</a>
[174]	2020	TensorFlow, Keras	Road Traffic Speed	<a href="https://github.com/RomainLITUD/DGCN_traffic_forecasting">https://github.com/RomainLITUD/DGCN_traffic_forecasting</a>
[179]	2020	PyTorch	Road Travel Time	<a href="https://github.com/YibinShen/TTPNet">https://github.com/YibinShen/TTPNet</a>
[185]	2020	TensorFlow	Time of Arrival	<a href="https://github.com/didi/heteta">https://github.com/didi/heteta</a>
[4]	2019	PyTorch	Road Traffic Speed	<a href="https://github.com/nanzhan/Graph-WaveNet">https://github.com/nanzhan/Graph-WaveNet</a>
[125]	2019	PyTorch	Road Traffic Speed	<a href="https://github.com/sshleifer/Graph-WaveNet">https://github.com/sshleifer/Graph-WaveNet</a>
[130]	2019	TensorFlow	Road Traffic Speed	<a href="https://github.com/lehaifeng/T-GCN">https://github.com/lehaifeng/T-GCN</a>
[131]	2019	TensorFlow	Road Traffic Speed	<a href="https://github.com/zhiyongc/Graph_Convolutional_LSTM">https://github.com/zhiyongc/Graph_Convolutional_LSTM</a>
[164], [165]	2019	MXNet	Road Traffic Speed	<a href="https://github.com/TobiasSkovgaardJepsen/relational-fusion-networks">https://github.com/TobiasSkovgaardJepsen/relational-fusion-networks</a>
[3]	2018	TensorFlow	Road Traffic Speed	<a href="https://github.com/liyaguang/DCRNN">https://github.com/liyaguang/DCRNN</a>
[3]	2018	PyTorch	Road Traffic Speed	<a href="https://github.com/chnsh/DCRNN_PyTorch">https://github.com/chnsh/DCRNN_PyTorch</a>
[110]	2018	MXNet	Road Traffic Speed	<a href="https://github.com/jennyzhang0215/GaAN">https://github.com/jennyzhang0215/GaAN</a>
[169]	2018	TensorFlow	Road Traffic Speed	<a href="https://github.com/JingqingZ/BaiduTraffic">https://github.com/JingqingZ/BaiduTraffic</a>
[181], [182]	2018	TensorFlow	Traffic Congestion	<a href="https://github.com/sudatta0993/Dynamic-Congestion-Prediction">https://github.com/sudatta0993/Dynamic-Congestion-Prediction</a>

TABLE VIII  
OPEN SOURCE PROJECTS FOR TRAFFIC DEMAND RELATED PROBLEMS.

Article	Year	Framework	Problem	Link
[199]	2020	TensorFlow	Taxi Demand	<a href="https://github.com/hujilin1229/od-pred">https://github.com/hujilin1229/od-pred</a>
[202]	2020	TensorFlow, PyTorch	Taxi Demand	<a href="https://github.com/NDavisK/Grids-versus-Graphs">https://github.com/NDavisK/Grids-versus-Graphs</a>
[207]	2020	PyTorch	Taxi Demand, Bike Demand	<a href="https://github.com/Essaim/CGCDemandPrediction">https://github.com/Essaim/CGCDemandPrediction</a>
[192]	2019	TensorFlow, Keras	Ride-hailing Demand, Bike Demand, Taxi Demand	<a href="https://github.com/LeeDoYup/TGGNet-keras">https://github.com/LeeDoYup/TGGNet-keras</a>
[198]	2019	Keras	Taxi Demand	<a href="https://github.com/kejintao/ST-ED-RMGC">https://github.com/kejintao/ST-ED-RMGC</a>

year ideally), have been discussed in previous surveys [11]. Compiling a centralized and standardized data repository is particularly challenging for GNN-based models where natural graphs are collected and stored in a variety of data formats (e.g. Esri Shapefile and OSM XML used by Openstreetmap

are used for digital maps in the GIS community) and various different similarity graphs can be constructed from the same traffic data in different models.

Some previous attempts in this direction have been made in the machine learning community, e.g. setting benchmarks for

TABLE IX  
OPEN SOURCE PROJECTS FOR OTHER PROBLEMS.

Article	Year	Framework	Problem	Link
[217]	2020	TensorFlow	Traffic Accident	<a href="https://github.com/zzyy0929/AAAI2020-RiskOracle/">https://github.com/zzyy0929/AAAI2020-RiskOracle/</a>
[218]	2020	PyTorch, DGL	Traffic Accident	<a href="https://github.com/yule-BUAA/DSTGCN">https://github.com/yule-BUAA/DSTGCN</a>
[224]	2020	PyTorch, DGL	Parking Availability	<a href="https://github.com/Vvrep/SHARE-parking_availability_prediction-Pytorch">https://github.com/Vvrep/SHARE-parking_availability_prediction-Pytorch</a>
[225]	2020	TensorFlow	Transportation Resilience	<a href="https://github.com/Charles117/resilience_shenzhen">https://github.com/Charles117/resilience_shenzhen</a>
[228]	2019	TensorFlow, Keras	Lane Occupancy	<a href="https://github.com/mawright/trafficgraphnn">https://github.com/mawright/trafficgraphnn</a>

several traffic prediction tasks in Papers With Code <sup>24</sup>, and in data science competitions, e.g., the Traffic4cast competition series <sup>25</sup>. However, the realization of a centralized data repository remains an open challenge.

2) *Combination with Other Techniques*: GNNs may be combined with other advanced techniques to overcome some of their inherent challenges and achieve better performance.

*Data Augmentation*. Data augmentation has been proven effective for boosting the performance of deep learning models, e.g. in image classification tasks. However, due to the complex structure of graphs, it is more challenging to apply data augmentation techniques to GNNs. Recently, data augmentation for GNNs has proven helpful in semi-supervised node classification tasks [251]. However, it remains a question whether data augmentation may be effective in traffic forecasting GNN applications.

*Transfer Learning*. Transfer learning utilizes knowledge or models trained for one task to solve related tasks, especially those with limited data. In the image classification field, pre-trained deep learning models from the ImageNet or MS COCO datasets are widely used in other problems. In traffic prediction problems, where a lack of historical data is a frequent problem, transfer learning is a possible solution. A novel transfer learning approach for DCRNN is proposed in [147], so that a model trained on data-rich regions of highway network can be used to predict traffic on unseen regions of the highway network. The authors demonstrated the efficacy of model transferability between the San Francisco and Los Angeles regions using different parts of the California road network from the PeMS.

*Meta-learning*. Meta-learning, or learning how to learn, has recently become a potential learning paradigm that can absorb information from a task and effectively generalize it to an unseen task. There are different types of meta learning methods and some of them are combined with graph structures for describing relationships between tasks or data samples [252], [253]. Based on a deep meta learning method called network weight generation, ST-MetaNet<sup>+</sup> is proposed in [25], which leverages the meta knowledge extracted from geo-graph attributes and dynamic traffic context learned from traffic states to generate the parameter weights in graph attention networks and RNNs, so that the inherent relationships between diverse types of spatiotemporal correlations and geo-graph attributes can be captured.

*Generative Adversarial Network (GAN)* [254]. GAN is a machine learning framework that has two components, namely, a generator, which learns to generate plausible data, and a

discriminator, which learns to distinguish the generator’s fake data from real data. After training to a state of Nash equilibrium, the generator may generate undistinguished data, which helps to expand the training data size for many problems, including those in the traffic domain. In [22], the road network is used directly as the graph, in which the nodes are road state detectors and the edges are built based on their adjacent links. DeepWalk is used to embed the graph and the road traffic state sensor information is transferred into a low-dimensional space. Then, the Wasserstein GAN (WGAN) [255] is used to train the traffic state data distribution and generate predicted results. Both public traffic flow (i.e., Caltrans PeMSD7) and traffic speed (i.e., METR-LA) datasets are used for evaluation, and the results demonstrate the effectiveness of the GAN-based solution.

*Automated Machine Learning (AutoML)*. The application of machine learning requires considerable manual intervention in various aspects of the process, including feature extraction, model selection, and parameter adjustment. AutoML automatically learns the important steps related to features, models, optimization, and evaluation, so that machine learning models can be applied without manual intervention. AutoML would help to improve the implementation of machine learning models, including GNNs. An early attempt to combine AutoML with GNNs for traffic prediction problems is an Auto-STGCN algorithm, proposed in [62]. This algorithm searches the parameter space for STGCN models quickly based on reinforcement learning and generates optimal models automatically for specific scenarios.

*Bayesian Network*. Most of the existing studies aim for deterministic models that make mean predictions. However, some traffic applications rely on uncertainty estimates for the future situations. To tackle this gap, the Bayesian network, which is a type of probabilistic graphical model using Bayesian inference for probability computations, is a promising solution. A similar alternative is Quantile Regression, which estimates the quantile function of a distribution at chosen points, combined with Graph WaveNet for uncertainty estimates [170].

## VII. CONCLUSION

In this paper, a comprehensive review of the application of GNNs for traffic forecasting is presented. Three levels of traffic problems and graphs are summarized, namely, road-level, region-level and station-level. The usages of recurrent GNNs, convolutional GNNs and graph autoencoders are discussed. We also give the latest collection of open dataset and code resource for this topic. Challenges and future directions are further pointed out for the following research.

<sup>24</sup><https://paperswithcode.com/task/traffic-prediction>

<sup>25</sup><https://www.iarai.ac.at/traffic4cast/>

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